Credit Risk Modeling Techniques for Life Insurers

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Executive Summary

The Society of Actuaries (SOA) engaged Kamakura Corporation to help illuminate credit risk modeling techniques within the life insurance industry. This involved a review of available research on the subject from academic and industry sources, the development and distribution of a survey on actual techniques used within the industry, and all associated analysis.

The finance and economics literature review provides a historical review of academic research on credit modeling beginning with Altman Z-scores, Merton's structural model and more recent "reduced form models." The industry literature includes discussions of the various credit modeling techniques, factor-based approaches, credit migration models, structural models, reduced form models, hybrid models, actuarial models and credit scoring models.

As credit risk modeling is an extremely broad topic, the scope of the survey is narrowed to particular asset classes and functions. We explore the data to identify what characteristics about a firm appear to coincide with the robustness and complexity of their approach to credit risk. There were 22 respondents in total to the survey from locations in Canada, Europe and the United States. We found that "large" firms (above median size) and "quantitative" firms (defined in the report) behaved substantively differently than “small” and “non-quantitative” firms, respectively, in a variety of credit risk contexts, including portfolio composition and modeling approaches, as well as model applications, robustness, and versatility.

In total, larger firms seem to hold more complex securities, which require more credit analysis and are more modeling-intensive. U.S. firms hold more complex, credit-risky assets and a higher share of assets that have traditionally been the focus of credit risk, though sovereign credits are now facing dramatically increased scrutiny throughout the industry. The most common credit models are "Historical credit assessment based on internal ratings or rating agency data" used by 86 percent of the companies, followed by "Factor-based approach—Historical Averages" used by 77 percent of firms. Fifty percent of firms used some form of more advanced quantitative approach, with the most popular being "transition matrix" followed by "structural models." Of note, 27 percent of firms have developed or are developing some type of internal proprietary model. Much like larger firms, firms with more quantitative credit approaches are also more likely to hold more analytically challenging securities in their portfolio. Larger and more quantitative firms are also more likely to use different applications of credit modeling, whether it be deterministic, stochastic, stress testing or sensitivity testing. Almost all of the respondents with non-quantitative methods did not incorporate the seniority of a security into their modeling, while all of the quantitative respondents took this into account in some fashion. Finally, larger firms and more quantitative firms are more likely to employ credit risk in almost every actuarial function, including multiperiod projections of credit risk. Most firms indicated that different modeling approaches are appropriate for different objectives or types of analysis, and they report either no constraints in their current modeling approach, or that they are constrained by people or budget issues. With respect to future modeling improvements, most quantitative companies have specific lists of planned improvements. Most non-quantitative companies have no stated plans or only vague comments on their

planned improvements. Despite these differences across firms, respondents seemed to broadly agree on common elements in the characterization of "best practice," including: [1]

- Multiple credit models that include a wide range of risk drivers and the capability to examine the sensitivity of each on the cash flow and credit risk of each security and the portfolio.
- Models that can reflect a range of correlations assumptions between key risk drivers.
- Models have the ability to examine risks under multiple time horizons, including multi-step horizons, and at a variety of confidence intervals.
- Stochastic models with the ability to produce full loss distributions and perform stress tests.
- Credit models that are incorporated into an integrated asset/liability framework.
- Key assumptions, as well as the models themselves, are understood by both modelers and management, and the models provide actionable information to all interested parties.

While it does not appear that any insurance company, or any financial firm for that matter, can reasonably claim to satisfy all of the elements of "best practice" listed above, some insurers are reasonably close. However, many—if not most—are not. Often, firms report that people or budget issues prohibit more intricate or more appropriate analysis. Somewhat surprisingly, the most common response in this regard is that modeling software does not exist. Despite this, we see several firms that are migrating to new software products and risk analysis firms over the next two years to help them accomplish these goals. Based on the survey responses, it is our opinion that the industry may benefit from increased communication amongst participants with respect to their preferred credit analysis software or consultants.

[1] Please note that when "best practice" is discussed in this document, it is in the context of the respondent's or the author's characterization, rather than the SOA's particular views or recommendations.

Introduction

How an institution models and accounts for credit behavior is one of the key inputs into projecting financial results and capital levels. Despite the importance of credit risk modeling, institutions often characterize credit risk through relatively simple default assumptions. The Society of Actuaries (SOA) Committee on Life Insurance Research, Committee on Finance Research and the Financial Reporting Section engaged Kamakura Corporation to conduct a research project to educate actuaries and other interested parties on the latest research on credit losses and defaults, as well as the current actuarial practices around modeling credit losses. This involved a review of available research on the subject from academic and industry sources, the development and distribution of a survey on actual techniques used within the industry, and all associated analysis.

This paper is divided into three parts. The first section describes developments in academic and industry research on credit modeling techniques, paying particular attention to the gradual expansion of credit risk issues and current best-practice methodologies. The second section describes the survey that was distributed by Kamakura Corporation and the SOA to industry participants along with a summary of the results. In the final section, we present our conclusions and commentary.

Acknowledgments

Kamakura would like to thank all 22 survey participants for their time and effort in completing the survey. We found the responses to be very illuminating. The participants are identified in the "Survey" section of this paper. We would also like to thank all of the members of the SOA's Project Oversight Group for their significant contributions:

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Literature Review

This section discusses the evolution of academic and industry credit modeling research in economics, finance and insurance. This is not meant as a complete summary of such a vast body of work, but is intended instead to motivate the analysis surrounding the survey responses later in this document.

This literature review covers recent developments in credit risk modeling in top-tier actuarial, economic, econometric and financial peer-reviewed journals. The survey includes work from the theoretical, empirical and practitioner space covering default modeling, loss given default, and the evaluation of interest rate and credit risk in a unified framework. A partial listing of examined peer-reviewed sources includes: *The North American Actuarial Journal, The Quarterly Journal of Economics, Econometrica, American Economic Review, Journal of Economic Theory, Journal of Econometrics, Review of Economic Studies, Journal of Applied Econometrics, Journal of Financial Economics, Applied Financial Economics, Applied Mathematical Finance, The Journal of Financial and Quantitative Analysis* and *The Journal of Financial Economics*. We also include appropriate material from the American Academy of Actuaries' Standards of Practice, Society of Actuaries, Association for Investment Management and Research, as well as several presentations from risk management conferences. Of course, special attention is given to papers that are heavily cited by subsequent work, as well as especially recent publications. Candidate papers from industry were found on the SOA website and CFA Institute website using a search function for "credit risk modeling" or "credit modeling." Search results were then scanned for papers of interest. For the purposes of this review, we first focus on the economics and finance literature, paying special attention to historically important articles, those that were first to illustrate how to incorporate credit risk in particular ways, and any that shed light on the relative merits of a particular approach. Following this, we discuss insurance and industry-specific research, including journal publications, presentations, and industry assessments.

Economics and Finance Literature: Historical Perspective

The quantitative credit analysis literature began with Altman (1968), where the author proposes discriminant analysis to determine combinations of observable characteristics that may best differentiate between defaulted and non-defaulted firms. This paper was one of the first examples of a quantitative, "credit-scoring" approach to credit assessment. This approach has fallen out of favor in recent decades, in part because of the descriptive focus. Discriminant analysis characterizes a firm's likely observable characteristics given the current default status, while a credit analyst is generally interested in the converse: a firm's likely default status given its observable characteristics. In addition to this point, Lo (1986) proves that discriminant analysis is consistent in a much more limited set of circumstances relative to other, more modern approaches. One such approach is logistic regression models that afford a methodology to estimate directly the effects of particular variables on default probabilities (or in the case of logistic regression, the log odds-ratios of the default probabilities).

The 1970s saw the broad application of stochastic calculus into the theoretical finance toolkit. This led to many breakthroughs throughout the field, including in the assessment of credit risk. Merton (1974) is the canonical example. In this paper, Merton applies the option-pricing framework from Black and Scholes (1973) to a firm's balance sheet. Given standard assumptions governing frictionless markets, full information, and the assumption that firms will default when and if their asset value falls below their liabilities, Merton demonstrates how one can calculate a default rate for any firm. These assumptions about the nature of the markets and the nature of economic behavior cause these models to be called "structural models." The additional structural assumptions allow the analyst to calculate credit risk given relatively parsimonious data requirements (one needed only the risk-free rate, and firm-level leverage, value of assets and volatility of assets), and the theoretical appeal of the assumed structure led to this model's wide acceptance and the development of further "structural" models of credit risk. Of course, further developments in the literature investigated the reasonableness of the key structural assumptions with fairly disappointing results (Shumway and Bharath (2008)).

With this foundation, the literature began to apply credit risk in new arenas and relax some key assumptions. Hull and White (1995) discuss how one can incorporate counterparty credit risk in derivative securities, while Duffie and Singleton (1999), and Jarrow and Turnbull (1997) focus on the dynamic nature of credit risk through credit spreads. Duffie and Singleton prove the uniqueness of credit spreads and apply them to a variety of contexts, including term structure models and derivative products; Jarrow and Turnbull develop a model that allows for dynamic credit spreads and calculate the associated impacts on pricing. Lando (1998) demonstrates how risk-free interest rates can be incorporated into quantitative credit analysis. This generalization dramatically increased the potential for quantitative default modeling: now, one can reasonably look at a variety of inputs or "state variables" when characterizing credit risk rather than asset value, volatility and leverage as in Merton (1974).

Shumway (2001) and Jarrow and Chava (2004) estimate flexible, "reduced form" models of default intensity that characterize default risk in a statistical model based on firm- and economy-level detail. Shumway notes that reduced form hazard models appear to have superior out-of-sample performance, and the additional information incorporated in the default prediction, such as size, historical stock returns, and the variation in stock returns all appear very important. Jarrow and Chava validate these results, apply this methodology to a monthly frequency for the first time, incorporate industry-level heterogeneity for the first time, and take Shumway's information conclusions a step further: it appears that given available market prices, standard accounting ratios (such as one would see in Altman (1968) or Merton (1974)) add fairly little explanatory power to default estimation equations. In their credit modeling summary, Altman, Resti, and Sironi (2004) reiterate Shumway's and Jarrow and Chava's findings on the sufficiency of the Merton structural approach in characterizing corporate default risk and the relative performance of structural and reduced form models in default modeling. However, the performance for recovery rates is more mixed. In the literature, recovery rate modeling is surrounded by data issues. In addition to the much smaller universe of data, recoveries also have timing issues and intra-firm heterogeneity across securities, as well as tremendous variation across firms and industries both at a point in as well as over time. Jarrow (2001) attempts to detangle default and recovery risk by examining debt and equity prices with the assumption that in the event of default, the equity value is zero. This is complicated somewhat by the variation in volume between these markets, which necessitates some way to incorporate liquidity risk and liquidity spreads, which we see in much more detail further in the decade. Araten, Jacobs and Varshney (2004) detail the results of an 18-year study of commercial loan recovery rates. They find that the distribution of recoveries tends to be bimodal, varies tremendously by industry and geography (though they do not have enough power to detect a statistical effect), and that the secured or unsecured nature of the credit seems to affect the macroeconomic sensitivity of the recovery rate. Altman (2006) discusses the need for recovery rates to be an independent variable for both structural and reduced form default probability models, as his research shows that there is a statistically significant inverse relationship between recovery and default rates. Finally, Guo, Jarrow, and Zeng (2009) develop a model for pricing distressed debt under default and recovery risk with complete and incomplete information.

Recent literature seems to favor the reduced form approach in data rich environments, such as corporate defaults. Shumway and Bharath (2008) demonstrate that structural models are outperformed by reduced form models to such an extent that it is possible to outperform Merton (1974) and its modern-day implementations both in-sample and out-of-sample with a much simpler alternative that does not require the stringent assumptions or simultaneous non-linear equations of the structural approach. Campbell, Hilscher and Szilagyi (2008) even illustrate how one can identify “distressed” firms based on observable characteristics and generate a profitable trading strategy through the application of reduced form models.

Recent developments in credit-related assets such as credit default swaps (CDS) have led to a great deal of academic work. Interestingly, much of the work on the CDS market focuses on the shortcomings of these market prices as sources of credit information rather than their strengths. Longstaff, Mithal, and Neis (2005) find that a substantial fraction of quoted corporate yield spreads (through the CDS market) can only be explained by an appeal to non-credit-related, or “liquidity” components. Jarrow (2012) describes how inferring default rates from CDS quotes is fraught with theoretical issues in addition to the empirical inadequacies. Finally, Campbell, Hilscher, and Szilagyi (2008) take issues with the efficiency of prices outside of the CDS market. They illustrate how one can use a reduced form framework to identify observably distressed firms, and then demonstrate that these distressed firms have lower-than-average returns, even after accounting for typical factors such as volatility and size.

Economics and Finance Literature: Current Consensus

The general consensus from the literature on the relative empirical performance of “structural” and “reduced form” default probability modeling, the relative accessibility of data and modeling software all combined to lead to a rapid expansion in the credit modeling literature in the mid-2000s. Cetin, Jarrow, Protter, and Yilidrim (2004) motivate a reduced form modeling approach through the lens of incomplete information. As the analyst does not observe the market value of the assets of the firm or their volatilities, a true implementation of Merton (1974) is impossible, and instead one would like to condition on as many observable covariates that are correlated with asset value and asset volatility as possible. Duffie, Wang, and Saita (2007) illustrate how to incorporate default risk that varies over time through a conditional term structure of default probabilities based on observable characteristics. This naturally leads to questions concerning correlation in default intensities over time. Das, Duffie, Kapadia, and Saita (2007) and Jarrow and van Deventer (2005) examine endogenous correlation in a reduced form model through dependence on common covariates. After the recession of the late 2000s, regulatory agencies have focused a great deal of energy on incorporating macroeconomic sensitivity into credit models. Reduced form models are naturally suited to this approach as well. In fact, Figlewski, Frydman, and Liang (2012) demonstrate the sensitivity of default rates to common macroeconomic variables *within a given ratings grade*, suggesting that ratings themselves are not well suited to this new focus.

Modern quantitative credit risk modeling in economics and finance has evolved from describing observable characteristics of defaulted firms to inferring default intensities by assuming a certain structure to the markets and to the underlying processes that govern asset values, and finally to a point where the analyst can broadly describe and accurately estimate an entire high frequency term structure of default probabilities with endogenous cross-sectional default correlations through reliance on a generalized set of observable characteristics, including macroeconomic factors. More than that, recent research trends have also highlighted potential pitfalls for the conscientious analyst when inferring credit parameters from certain market prices. Still, there is a great deal of research to be done outside of the corporate default space, where data quality and/or availability concerns slow the rate of academic research.

Industry Literature: Principal Sources

Interestingly, the applied and insurance industry research has followed a much more diverse trend. Some organizations and publications have had fairly light coverage of credit, or have only recently begun to include credit research, though this is certainly not the case across the board.

Industry organizations place a great deal of emphasis on credit risk. The American Academy of Actuaries Actuarial Standards of Practice, while not recommending any particular models, require the actuary to consider the impact on cash flow associated with asset quality and the risk of asset default. The SOA exam syllabus includes knowledge of both structural and reduced form models, loss given default, correlation, and credit derivatives. The National Association of Insurance Commissioners (NAIC) has hired third parties to provide risk-based capital factors for structured products and published their methodologies. Historically, there has not been much credit risk research in the *North American Actuarial Journal*, as discussed in an editorial by Li (2006). However, this appears to be changing. In 2008, two papers were published, "The Pricing of Credit Default Swaps under a Markov-Modulated Merton's Structural Model" (Sui et al., 2008) and "Computation of Multivariate Barrier Crossing

Probability and Its Applications in Credit Risk Models" (Huh and Kolkiewicz, 2008). In Sui, the authors relax assumptions regarding fixed interest rates, fixed volatilities and fixed leverage from the Merton model for the valuation of CDS contracts. In Huh and Kolkiewicz, the authors demonstrate a computationally efficient way of pricing CDS contracts with several reference entities using a structural model.

In contrast, the SOA literature includes discussions of the various credit modeling techniques, factor-based approaches, credit migration models, structural models, reduced form models, hybrid models, actuarial models and credit scoring models. Several articles provide a brief survey of the various models. Other articles provide in-depth discussion of a particular type of model. Ten Lohuis and Narayanan's (2004) presentation at the 2004 Investment Actuary Symposium provides an excellent introduction describing how two insurers view and apply credit risk modeling. Farr et al. (2008) provide a brief discussion of various modeling methods, including factor-based approaches, applications of structural and stochastic models, the interaction of assets and liabilities, and stress tests for credit spread modeling. Industry practice is often its own area of independent interest and research: Buff (1992), in the context of asset and liability management, presents a way to study default risk using interactive cash-flow projections of assets and liabilities that are computed along a set of scenarios of default rates. Zurcher (1993) discusses the stochastic modeling and "select/ultimate" default rates used to develop the original bond RBC C-1 factors. Shipperlee (2006) provides presentation slides for an introductory review of how insurance companies manage credit risk. The presentation discusses probability of default, loss given default, credit scoring and data issues. Megregian et al. (2010) find that among surveyed companies, a "reduction to yield" is the most popular way to reflect asset default in pricing, although the smallest companies consider asset default as not material. Sharpe (2011) has a presentation covering governance tools for credit risk management, probability of default, loss given default, rating transitions, simulation, valuation at horizon, credit earnings at risk, and appendix to determine correlations.

Whilst they were almost entirely absent from the economics and finance literature, many industry articles discuss factor-based approaches, including incidence and severity models. Luckner and Young (1999) provide a case study that looks at credit risk using the incidence-and-severity model, and explicitly defines economic loss for a "credit risk event" as a ratio of the difference between the present value of cash flows with and without credit risk events divided by the present value of cash flows without credit risk events. Agency ratings also receive a great deal of focus, from simple Markov transition matrices to ordinal logistic regression and stochastic analysis. Hambro and Houghton (2001) provide a general introduction to interest rate and credit risk—deterministic and stochastic simulation, spreads, and the various types of credit-related risk, and deterministic modeling of credit risk using incidence-and-severity. Houghton also presents a stochastic modeling approach to credit risk that includes both asset default and downgrades using transition matrices. Bae and Kulpergry (2008) propose a multiperiod ordinal logistic regression model for credit rating transition probabilities. They extend single period factor based models to a multiperiod case. Han (2008) provides a historical perspective to both single-factor and multifactor credit models. He then demonstrates the use of one credit model to optimize a credit portfolio using multiple credit transition metrics.

Industry Literature: Reviews of Modeling Techniques

Reviews of techniques are also more common in investment industry literature. McLean (1998) traces the development of credit risk measurement methods over the 1977–1997 period, ranging from subjective to quantitative. Kao (1999) provides an overview of several methods, Altman Z-scores, statistical models, structural and reduced form models (both default-based and transition-matrix-based), and market implied models. Jarrow, as summarized by Smith (1998), provides a nontechnical overview of credit derivatives and computation methods for pricing them. Van Deventer (2005) compares structural, reduced form and hybrid models, tests them using the Receiver Operating Characteristic Accuracy Ratio, and supports using a multiple model approach, that is, both structural and various implementations of reduced form models. Lleo (2009) reviews five main credit risk measurement methodologies: credit migration, structural models, intensity models, actuarial approaches, and large portfolio models.

More quantitative techniques are discussed here as well. Le Roux, Shinnawl, and Rubin (2003) compare traditional factor-based models with structural credit models, particularly the Merton (1974) model. They also highlight the important distinction between individual credits versus a portfolio of credits and correlation among credits as a key discussion point. Das, Fong and Geng, as summarized by Horan (2002), find that ignoring correlation of defaults, and therefore the skewness and kurtosis of the loss distribution, would underestimate the risk of extreme outcomes. Leland, as summarized by Sullivan (2005), finds that studied structural models "underpredict defaults and yield spreads." Arora, Bohn, and Zhu, summarized by Phelps (2006), discuss the Merton model, Vasicek-Kealhofer and a reduced form model by Hull-White. The paper concludes that the Merton model underperforms the other two. Bernard and Chen (2007) explore the interaction between regulatory requirements and the varying risk management strategies of an insurance company using a theoretical Merton model and make the point that the market valuation of liability contracts that ignore risk management strategies will be too low. Hui (2008) discusses the difficulties in modeling mortgage-backed securities (MBS) defaults and problems with historical data. Indeed, data reliability issues are the principal reason why one might prefer structural models as compared to reduced form models. Risk factors and reduced form approaches are present as well. Boudreault and Gauthier (2010) present a multi-name hybrid credit risk model where the default of each company is highly related to how elements of its capital structure evolve over time, how assets and liabilities of insurers are linked across firms, and possible resulting contagion effects. Rosen and Saunders (2010) study the contributions to the risk of a portfolio using risk factors rather than particular issuers, as has been done traditionally.

Finally, several papers provide cautions regarding modeling. Klein et al. (2009) view one of the causes of the financial crisis to be overreliance on third-party credit ratings by companies and regulators. Schoolman (2008) states that both Wall Street and insurers tend to underestimate risk, especially with respect to new, innovative securities and warns that historical data should include stressed periods, and model review should include specific stresses (particularly on correlation assumptions).[2] Derman (2009) provides a caution regarding the overreliance on models, "To confuse the model with the world is to embrace a future disaster driven by the belief that humans obey mathematical rules."

[2] Schoolman has a particularly compelling allegory to illustrate this point: “Every day of its life, when a turkey sees the farmer, it gets fed. Based upon that experience, when the turkey sees the farmer coming out of the farmhouse the day before Thanksgiving, it sees no reasons to be concerned. This very big error in judgment regarding the risk posed by the farmer is driven by the fact that the turkey’s prior experience period did not include a Thanksgiving. What Thanksgiving is your model potentially missing? What are you doing to address it?” This shortcoming of models calibrated to historical data was also a common survey response.

Overview and Survey Participants

As credit risk modeling is an extremely broad topic, the scope of the survey was narrowed to particular asset classes and functions: asset classes to be included in the survey responses are all credit sectors, bonds, loans, mortgages, and non-agency structured securities (MBS, asset-backed securities (ABS), commercial mortgage-backed securities (CMBS), collateralized debt obligations (CDOs)). Asset classes to be excluded in the survey responses are credit default swaps, futures, forwards, options, equity, currency, commodity, and hedge funds. For practical purposes, the survey also excluded counterparty credit risk, as this topic could easily stand alone as a research topic. The survey covered six main areas: firm provenance, portfolio allocation, credit-modeling approaches used in the organization, credit modeling applications within the organization, credit modeling assumptions and variables, and future credit modeling goals.

In addition to the literature detailed in the previous section, the literature in the SOA's research library provided a basis for the creation of the survey, both in terms of credit risk models that could be employed (including both structural and reduced form models), but also in the specific applications of credit risk modeling. Luckner and Young (1999), Hambro and Houghton (2001), ten Lohuis and Narayanan (2004), and Shipperlee (2006) provide reviews of different modeling methods.

The ultimate goal of the survey is to educate actuarial professionals on current practices regarding credit risk modeling in the life insurance industry. More than that, we explore the data to identify what characteristics about a firm, if any, appear to determine the robustness and complexity of its approach to credit risk. In this section, we will detail each question in the survey, summarize the responses, and characterize the respondents based on their answers to investigate potential reasons for any differences in credit techniques around the industry.

There were 22 respondents in total to the survey from locations in Canada, Europe and the United States. The full list of participating organizations is as follows:

1. Allstate Financial
2. American National Insurance Company
3. American-Amicable Life Insurance Company of Texas (and affiliate companies)
4. Cigna
5. CNO Financial
6. Farmers New World Life Insurance Company
7. Forethought Financial Group
8. Genworth Financial
9. Great-West Life & Annuity Insurance Company
10. Hartford Financial
11. Homesteaders Life Company
12. ING Insurance US
13. Nationwide Insurance Company
14. New York Life Insurance
15. Pacific Life

16. Principal Financial Group
17. Sun Life Financial
18. Symetra Life Insurance Company
19. Thrivent Financial for Lutherans
20. USAA Life Insurance Company
21. Vantis Life Insurance Company
22. Western & Southern Financial Group

Survey respondents represent a range of sizes and regulatory regimes. Mean respondent asset size is just below 50 billion USD (median is 34 billion), though the minimum size is less than 1 billion, and the maximum size is 240 billion. Half of the respondents are public firms, and roughly one-quarter each are organized as private firms and mutual firms, respectively. Most are from the United States, though there are several survey respondents that represent a U.S. subsidiary of a European or Canadian parent organization.

Respondents have varied approaches to characterizing credit risk. We found that firms utilizing different credit risk modeling techniques have materially different responses throughout the survey, including the applications of credit risk, research agendas, portfolio allocations, and the presence and/or severity of any institutional constraints. Public stock, private stock and mutual tended not to be key differentiators of how firms model credit risk, nor did the provenance of the parent organization. Two stratifications of the data that we found significant were "large" firms (above median size) relative to small firms and "quantitative" firms versus non-quantitative firms. We define “quantitative” credit modeling approaches as Credit Migration, Structural, Reduced Form, Hybrid, Actuarial, or Credit Scoring models, and “quantitative” firms as those who practice as least one “quantitative” credit modeling approach somewhere within the organization.

Sample Summary

Sample Stratification	Number of Firms	Average Total Assets	Number of Quantitative Firms	Number of U.S. Firms
Full Sample	22	49,954	11 (50%)	17 (77%)
Large Firms	11	85,606	8 (73%)	9 (82%)
Small Firms	11	14,301	3 (27%)	8 (73%)
Quantitative Firms	11	80,884	11 (50%)	8 (73%)
Non-Quantitative Firms	11	19,023	0 (0 %)	2 (18%)

Survey Responses

Throughout this section, asset values are measured in millions of USD unless otherwise indicated.

Contact Information

Q1: Name

Q2: Email

Q3: Company Name

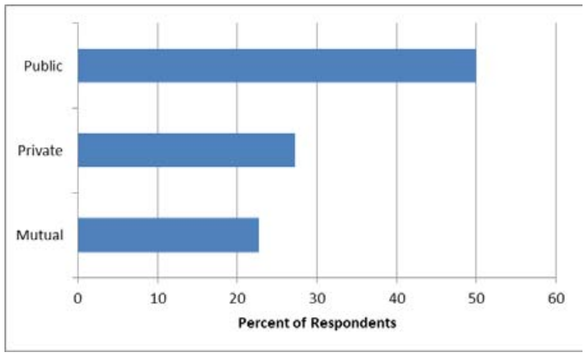
Q4: Phone Number

Q5: Type of Company (Insurance, Bank, Regulator)

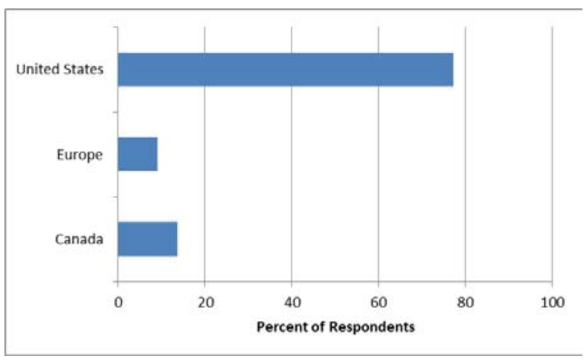
Potential identifying information from Q1 through Q5 was redacted upon receipt of the survey responses by the SOA.

In-Scope Functions and Assets

Q6: Is the company a mutual or a public insurance company?



Q7: What is the location of the parent company?



Q8: I am responding for the total company or for particular line(s) of business or for particular function(s) within the company.

Twenty of the 22 respondents indicated that they were responding for the total company.

Q9: Which specific line of business or function?

The two respondents that did not represent the total company both indicated that they represented the U.S. insurance subsidiary within the larger organization.

Q10: What is the total dollar value (in millions) of all assets of the company/consolidated group selected in Q6 according to the firm's most recent financial statements?

Measure	Total Asset Size in USD
Minimum	0.8 billion
Median	34 billion
Mean	50 billion
Maximum	240 billion

Q11: For the credit-risky assets described as in-scope above, please complete the following table including the dollar amount (in millions) of statutory asset values at 12/31/2011:

Average Percentage of Total Itemized Asset Holdings:

Asset Class	Combined Sample	Bottom 50% by Total Assets	Top 50% by Total Assets
U.S. Treasuries	3.2%	3.3%	3.1%
Sovereigns other than U.S. Treasuries	2.2%	1.9%	2.5%
Agency structured securities (MBS)	6.5%	7.8%	5.2%
Private label structured securities—MBS	4.1%	3.3%	4.9%
Private label structured securities—ABS	3.0%	1.3%	4.5%
Private label structured securities—CMBS	3.1%	1.5%	4.6%
Direct or whole residential mortgages	0.1%	0.0%	0.2%
Direct or whole commercial mortgages	11.2%	10.0%	12.3%
Direct or whole agricultural mortgages	0.0%	0.0%	0.0%
Other public bonds	48.7%	53.5%	44.3%
Other private bonds	13.1%	11.3%	14.7%

By far, the largest concentrations are in other public and private bonds (typically large corporates) and commercial mortgages. Small firms seem to hold more other public bonds, and smaller firms have slightly fewer commercial mortgages and private bonds. Larger firms also seem more likely to hold a larger portion of the portfolio in structured securities, and the combined overall portfolio share for all non-agency structured products is 14.1 percent, slightly larger than the portfolio share of commercial loans. In contrast, smaller firms have less than half of that share, at only 6.1 percent.

In total, from a credit-modeling perspective, larger firms seem to hold more complex securities: securities which require more analysis and are more modeling-intensive.

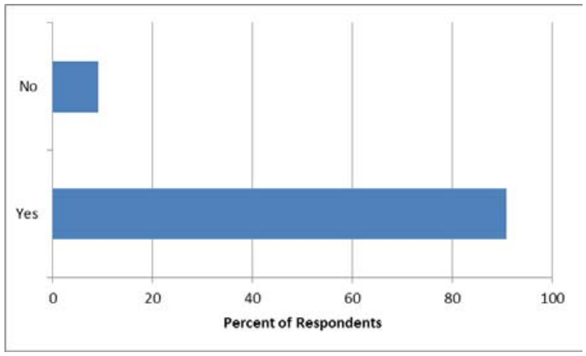
By Country of Origin:

Asset Class	Combined Sample	U.S. Respondents	Non-U.S. Respondents
U.S. Treasuries	3.2%	1.8%	7.6%
Sovereigns other than U.S. Treasuries	2.2%	1.3%	5.0%
Agency structured securities (MBS)	6.5%	6.5%	6.2%
Private label structured securities—MBS	4.1%	4.4%	3.4%
Private label structured securities—ABS	3.0%	3.3%	2.1%
Private label structured securities—CMBS	3.1%	3.5%	2.0%
Direct or whole residential mortgages	0.1%	1.0%	0.0%
Direct or whole commercial mortgages	11.2%	11.1%	11.4%
Other public bonds	48.7%	50.8%	42.0%
Other private bonds	13.1%	12.4%	15.3%

Non-U.S. firms hold much more sovereign debt (U.S. and otherwise) than U.S. firms, with the combined total of 12.6 percent versus U.S. firms' total of only 3.2 percent. U.S. firms make up this difference in the non-agency structured (11.1 percent versus 7.4 percent) and other public bonds space (50.8 percent versus 42.0 percent).

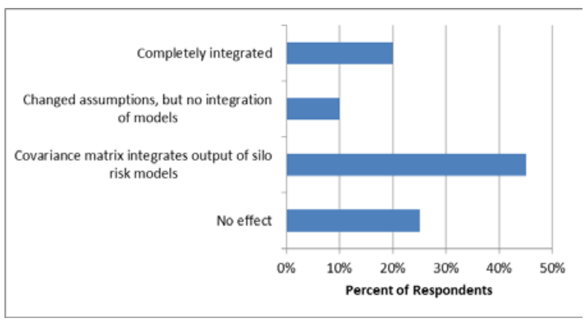
Based on these portfolio allocations, U.S. firms hold more complex, credit-risky assets and a higher share of assets that have traditionally been the focus of credit risk, though sovereign credits are now facing dramatically increased scrutiny throughout the industry.

Q12: Does your company currently practice enterprise risk management (ERM)?



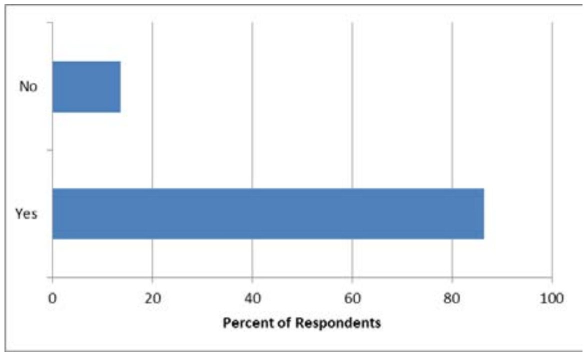
Only two firms did not say that they practice some form of ERM. Both of these firms are below the median in size (34 billion).

Q13: If yes, does ERM affect your conceptual or operational modeling approach to credit risk management? How?

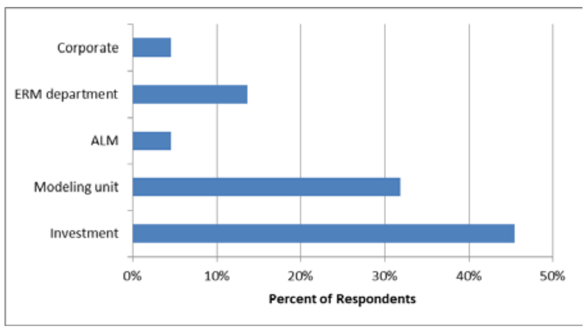


The most common approach to ERM was to attempt an ex-post integration of stand-alone models and model outputs. Roughly as many firms apply a completely integrated modeling approach with unified assumptions as those that report having no impact of ERM on their risk operations whatsoever.

Q14: Is there a centralized unit or center of excellence that handles, reviews or integrates all of the credit risk modeling issues within the company?

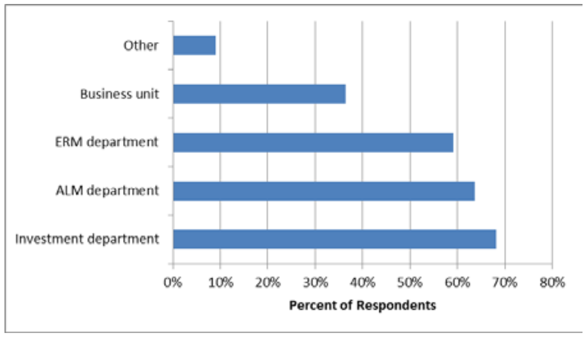


Q15: Does responsibility for credit risk modeling assumptions lie within the modeling unit(s) or another unit?



The organizations with their own ERM department are all well above the median (34 billion) in size. From the response to Q14, we know that 86 percent of respondents have a single center of excellence, though it seems the credit assumptions that are discussed in Q15 are set at various levels within the organization, including at the modeling unit itself. In short, the actual duties of the center of excellence may substantively vary across firms. All of the firms with more centralized groups, the ERM or ALM departments, are above the median in terms of size.

Q16: If another unit is responsible for credit risk modeling assumptions, please name the unit.
Q17: Which unit or units perform credit risk modeling?



It seems that the Investment, ALM, and ERM departments are the primary location for credit risk modeling, though, by far, the Investment unit is a more common location for setting credit assumptions themselves (Q15). The two other responses represented “Corporate Investment,” and “Actuarial” groups.

Q18: There are different types of credit models. Which of the following models are used for at least one function within the company? Please check all categories that are employed by the firm in some capacity. Note that we redact responses if they may be used to identify specific survey participants.

Mean Use Rates—All Firms (Asset size is measured in millions of USD.)

Model	Percent Using	Mean Asset Size Using	Mean Asset Size Not Using
None—defaults not material	4.6%	[redacted]	[redacted]
Factor-based approach (exposure times loss rate)—historical averages	77.3%	52,335	41,856
Historical credit assessment based on internal ratings or rating agency data. Examples: Bond migration studies, C-1 Risk-Based Capital approach	86.4%	55,632	13,991
Credit migration model—"Consider not only the risk of default, but also the risk that an investment will lose (or gain) value due to changes in the corporation's credit rating" (IAA). Examples: Ratings transition matrix, binomial/trinomial lattice	50.0%	80,884	19,023
Structural models—"Probability that a firm's asset value will fall below the level of the firm's liabilities" (Girling). Example: classical Merton models	27.3%	95,293	32,951
Reduced form models—"Obtain risk neutral default probability (market price of default)" (Girling). May also be known as "intensity models." Examples: logistic regression, macroeconomic factor-based modeling	9.1%	[redacted]	[redacted]
Hybrid models—"Incorporate all the predictive variables that go into the reduced form technology but that include the Merton default probability as an additional input" (van Deventer)	4.6%	[redacted]	[redacted]

Model	Percent Using	Mean Asset Size Using	Mean Asset Size Not Using
Actuarial credit models—"Use techniques from actuarial sciences to model the occurrence of default in large bond or loan portfolios. To derive a probability distribution for the credit loss of a portfolio," one well-known model, "first models the frequency of defaults, assuming that the probability distribution of the number of defaults in the portfolio follows a Poisson distribution." The model "then applies a loss given default to each default event. The parameters required in the analysis are estimated by using historical statistical data." (Sébastien Lleo)	13.6%	103,684	41,470
Credit scoring—"Scoring models summarize available, relevant information about consumers and reduce the information into a set of ordered categories (scores) that foretell an outcome." (FDIC)	4.6%	[redacted]	[redacted]
Other models (not internally developed)	22.7%	84,258	39,864
Proprietary internal model not included above	27.3%	81,689	38,053

For the remainder of this survey, we will examine firms in part based on their responses to this question regarding their credit modeling approach. We will define "quantitative" companies as any who use at least one of the following approaches to modeling credit risk: Credit migration, structural, reduced form, hybrid, actuarial, or credit scoring models. "Non-quantitative" companies are those that do not utilize any of the "quantitative" techniques listed above. "Non-quantitative" companies primarily use factor-based, historical assessment.

By this definition, 11 companies (50 percent of respondents) have a "quantitative" credit approach. Amongst small firms (below the median total asset size), 72.7 percent are non-quantitative; amongst large firms, it is exactly reversed, with 72.7 percent of large firms employing a quantitative approach somewhere within the organization. Larger companies also appear to utilize more modeling approaches. Also, by this definition, the firms that do not practice ERM (Q12) are "non-quantitative."

The next table describes the differences in asset allocation based on the firm's credit modeling approach.

Asset Allocation for Quantitative and Non-Quantitative Respondents (Defined in Q11):

Asset Class	Percent of Combined Sample	Percent of "Quantitative" Respondents	Percent of "Non-Quantitative" Respondents
U.S. Treasuries	3.2%	2.8%	3.5%
Sovereigns other than U.S. Treasuries	2.2%	3.6%	0.9%
Agency structured securities (MBS)	6.5%	5.9%	6.9%
Private label structured securities—MBS	4.1%	4.7%	3.6%
Private label structured securities—ABS	3.0%	3.4%	2.6%
Private label structured securities—CMBS	3.1%	4.1%	2.3%
Direct or whole residential mortgages	0.1%	0.2%	0.0%
Direct or whole commercial mortgages	11.2%	13.7%	8.9%
Direct or whole agricultural mortgages	0.0%	0.0%	0.0%
Other public bonds	48.7%	39.4%	57.2%
Other private bonds	13.1%	18.3%	8.3%

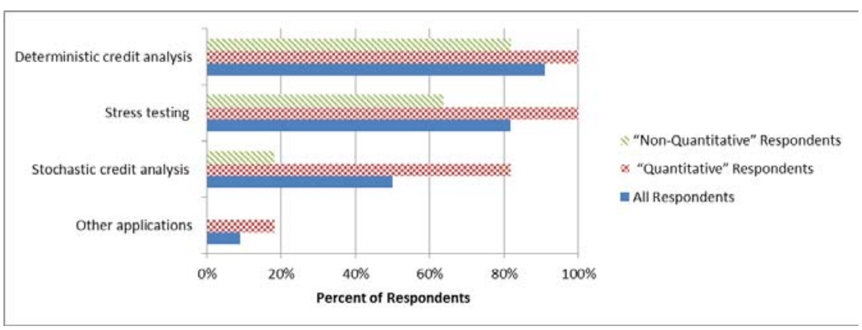
Firms with more quantitative modeling approaches hold more structured products (12.1 percent versus 8.5 percent), more commercial mortgages (13.7 percent versus 8.9 percent) and private bonds (18.3 percent versus 8.3 percent), and substantially fewer public bonds (39.4 percent versus 57.2 percent). Based on this information, it would appear that firms with more quantitative credit approaches are more likely to hold more analytically challenging securities in their portfolio. Of course, we cannot make a clear causal statement on this point. It is not clear if the capability to analyze complex securities creates the demand, or, alternatively, if the desire to purchase complex securities drives the improvements in modeling.

Q19: There are different applications of credit models. Which of the following applications of credit models are used for at least one function within the company? Please check all categories that are employed by the firm in some capacity.

Asset size is measured in millions of USD.

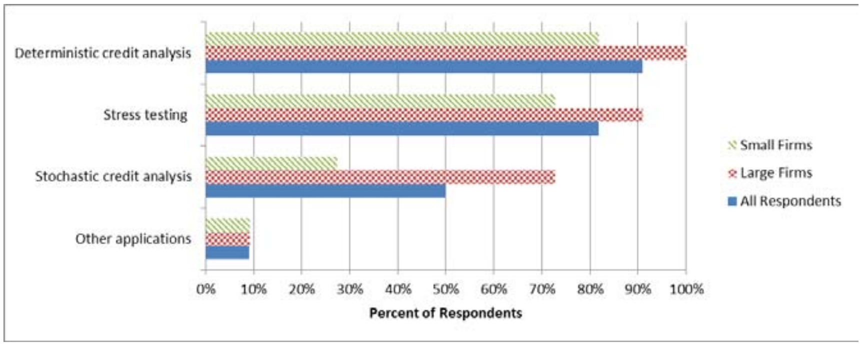
Type of Application	Percent Using	Mean Asset Size Using	Mean Asset Size Not Using
Deterministic credit analysis—Application where portfolio or subportfolio is subjected to fixed scenario(s), not necessarily extreme scenarios.	90.9%	53,668	12,811
Stress testing—Application where portfolio or subportfolio is subjected to fixed, extreme, scenario(s).	81.8%	56,935	18,536
Stochastic credit analysis—Application where portfolio or subportfolio is evaluated when credit risk factors are generated by a stochastic process.	50.0%	78,785	21,122
Other applications	9.1%	[redacted]	[redacted]

For almost every application, larger firms are more likely to use a given approach. The largest spread in terms of asset size is present for stochastic credit analysis, which is on its face the most intricate of the applications detailed above. Larger firms apply credit techniques in more ways, and in more complex ways, though application disparities are even more apparent based on the quantitative credit models distinction developed in Q18:



Quantitative firms use credit models for more applications in every respect. Again, this could be a function of the appropriateness of more quantitative models for more uses, or a desire for more uses requiring additional models, but in every respect we see that firms using more complex approaches apply credit models in more varied ways.

When we cut by firm size (large and small are defined as above and below the median in terms of total asset size), we note that the same patterns are still present, but of a smaller magnitude.



Q20: Does the company's credit risk modeling for at least one function include the following?

Asset size is measured in millions of USD.

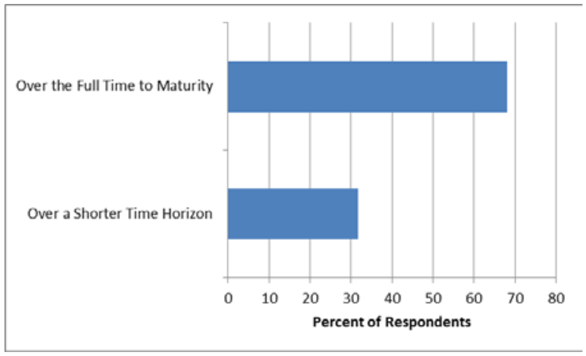
Component of Credit Risk	Percent Using	Mean Asset Size Using	Mean Asset Size Not Using
Recovery or loss given default	95.5%	50,660	35,108
Default probability	90.9%	51,955	29,940
Realized capital gains/losses	72.7%	48,273	54,435
Spread widening due to credit quality decline	45.5%	72,125	31,477
Unrealized capital gains/losses	40.9%	61,026	42,288
Spread widening other than due to credit quality decline	40.9%	39,031	57,515
Concentration: the overall distribution of assets across counterparties	40.9%	82,689	27,291
Sovereign—foreign government	40.9%	94,099	19,391
Settlement risk: the risk that a counterparty does not deliver on its obligations upon settlement	27.3%	50,098	49,899
Deferral of payment, that is the "risk that issuer may suspend dividends/coupons or the expected redemption schedule without triggering a default" (AIAWG)	18.2%	61,654	47,353

Almost all respondents use credit modeling for default probabilities, recovery rates, and realized gains and losses. In general, it appears that larger firms model more components of credit risk; though there are a few cases where small firms are more likely than large firms to model a particular component (Spread widening for non-credit reasons is a particularly noteworthy example.). Based on this table, one would be inclined to think that modeling of additional components is driven by scale in risk management applications, though variation in credit risk components also appears to be driven more by institution-wide credit approaches, as shown in the following table:

Component of Credit Risk	Percent Using	Percent of "Quantitative" Respondents	Percent of "Non-Quantitative" Respondents
Recovery or loss given default	95.5%	100%	90.9%
Default probability	90.9%	100%	81.8%
Realized capital gains/losses	72.7%	63.6%	81.8%
Spread widening due to credit quality decline	45.5%	63.6%	27.3%
Unrealized capital gains/losses	40.9%	45.5%	36.4%
Spread widening other than due to credit quality decline	40.9%	45.5%	36.4%
Concentration: the overall distribution of assets across counterparties	40.9%	72.7%	9.1%
Sovereign—foreign government	40.9%	81.8%	0.0%
Settlement risk: the risk that a counterparty does not deliver on its obligations upon settlement	27.3%	45.5%	9.1%
Deferral of payment, that is the "risk that issuer may suspend dividends/coupons or the expected redemption schedule without triggering a default" (AIAWG)	18.2%	27.3%	9.1%

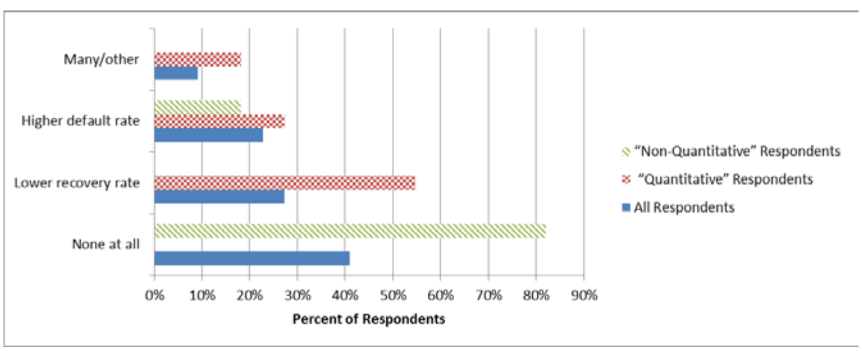
Quantitative firms are more likely to incorporate analysis of spread changes, concentration, deferral and settlement risks, and are the only firms that use credit risk when analyzing sovereign credits. However, as we saw in Q18, less quantitative firms hold a smaller amount of sovereign securities. The only component where non-quantitative firms are more prevalent is realized capital gains and losses. Less than one half of companies are estimating unrealized capital gains and losses or analyzing spread widening other than due to credit quality decline. There does not appear to be any difference between quantitative and non-quantitative firms in this respect.

Q21: Over what projection time period are you modeling the credit losses of the portfolio?



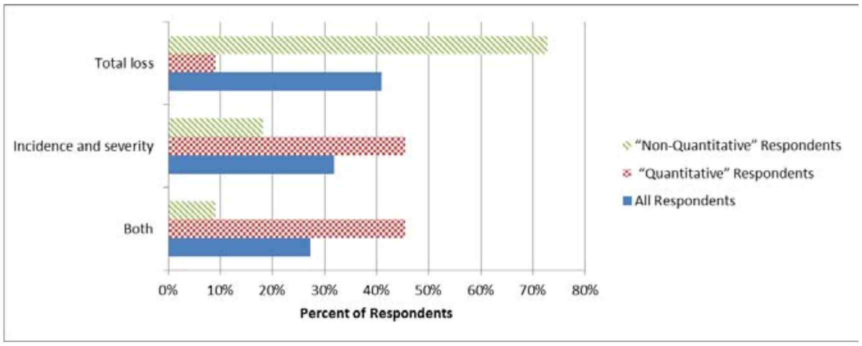
While projections over the full time to maturity will obviously be able to more accurately capture future events than if they were prematurely terminated, the sufficiency of this selection almost certainly depends on the particular application. Credit-adjusted value at risk, or short-term financial projections, could justify modeling credit losses over a time period shorter than the full maturity of the holding. Other applications, such as statutory cash flow testing, would appear to essentially require modeling to the maturity of the holding.

Q22: How, if at all, does the (lack of) seniority of a security within the capital structure of a company affect the company's credit modeling of that security? Here, we assume that "higher default rate" and "lower recovery rate" are each associated with "lower seniority" securities.



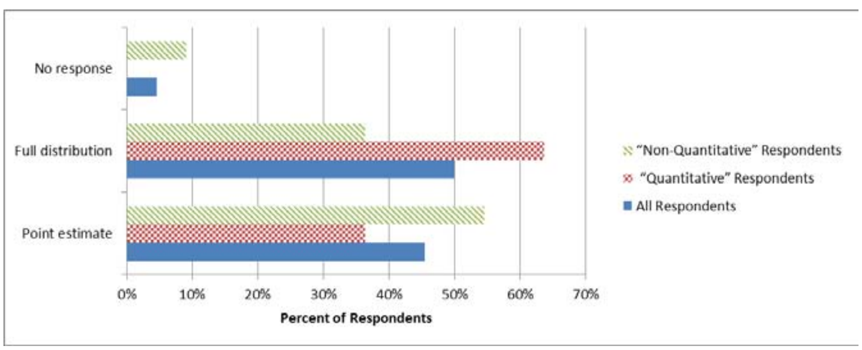
Almost all of the respondents with non-quantitative methods (from Q18) did not incorporate the seniority of a security into their modeling, while none of the quantitative respondents ignored this effect. Even further, the non-quantitative firms had seniority enter through an effect on default rates, while the quantitative firms had it impact recovery rates, which is a more realistic method for incorporating seniority.

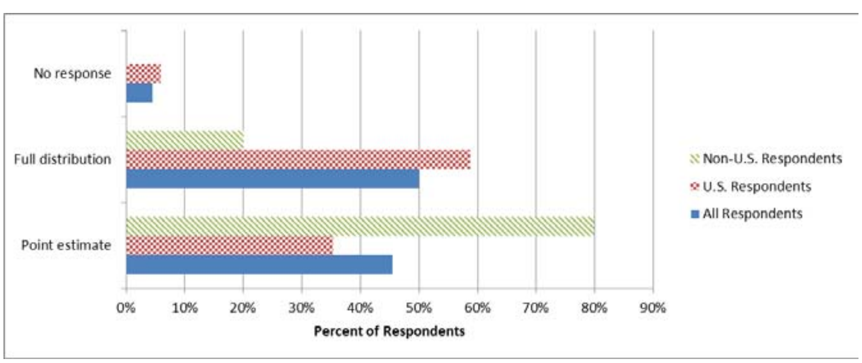
Q23: Does the company use incidence-and-severity or total loss models? (“Incidence”: the default probability; “severity”: the loss given default. When combined, they produce the total expected loss.)



We can see that almost all of the “quantitative” firms employ a more disaggregated view of credit losses within their portfolio. That is, almost all of the firms that utilize less complex credit models also have a less complex view of the composition of credit losses.

Q24: Are the models that determine a value for expected losses based on a point estimate or a full distribution of credit losses?





Recall from Q19 that only half of respondents used stochastic models. In Q24, we have 81.8 percent of respondents using the full distribution of credit losses also using stochastic credit models. This makes a great deal of sense, as stochastic credit models allow the analyst to simulate a distribution of potential outcomes through Monte Carlo analysis.

Q25: Are the models (Q17) that determine a value for expected losses based on performing specific stress test(s) or loss scenario(s)? Are the same scenarios employed across the institution?

Fourteen respondents (63.6 percent) indicated that they used institution-wide, common, specific scenarios to calculate the value for expected losses. Out of the respondents who did not use specific scenarios, many indicated that they calculated expected losses in some other fashion.

Functions that Use Credit Models

Q26: Credit risk modeling can be used for many different functions. Please refer to the table below when answering these questions: Does the company use credit risk modeling for the following functions? Please answer yes, no, or the company does not perform this function. If the company does modeling for this function, which type of model (from the table in Q19) is used for this function? Does the company use multiperiod models, or models where the default probability/loss rate vary across the projection period? For what functions are expected credit losses only determined? For what functions is the volatility of credit losses determined? For what functions are full distributions of credit losses simulated or calculated? Product development and pricing include the following functions: new business pricing, renewal credited rate determination, dividend scale work/closed block glide path, illustration actuary (actuary who certifies that life product sales illustrations assumptions are reasonable), and product development or ratemaking studies. Valuation includes the following functions: reserving, GAAP reserves and deferred acquisition cost (DAC), and FAS 157/159 and fair value of liabilities. Reserve adequacy includes GAAP loss recognition. Financial forecasting includes the following functions: SAP earnings projections and GAAP income projections.

Function	Percent of Yes Respondents	Mean Size of Yes Respondent	Mean Size of No Respondent
We use same models for all functions. (If so, just complete this row. If not, please complete the following rows.)	13.6%	1,235	57,646
Asset adequacy analysis/cash flow testing/reserve adequacy	86.4%	54,898	18,637
Product development and pricing	81.8%	56,969	18,384
Financial forecasting	81.8%	58,606	11,016
Determination of capital adequacy	81.8%	54,267	30,541
Asset-liability management (ALM)	77.3%	59,662	16,944
Economic capital	68.2%	66,458	14,587
NAIC C-1 RBC	63.6%	54,249	42,437
Valuation	54.6%	45,190	55,670
Embedded values	50.0%	62,843	37,063
M&A/actuarial appraisals	36.4%	48,055	51,039
Value at risk (VaR)	31.8%	85,512	33,359
Credit-adjusted value at risk (credit VaR)	31.8%	102,137	25,601
Risk-adjusted return on capital (RAROC)	27.3%	50,686	49,679

Note that, in this table, firms that do not claim to incorporate credit within a particular function may include firms that do not perform that function whatsoever. With that said, larger firms are more likely to employ credit risk in almost every function. Exceptions are valuation and M&A/actuarial appraisals (where the difference in size is particularly small). We see very large differences in size amongst firms conducting financial forecasting, VaR, credit VaR, economic capital, and ALM analysis. With the exception of Solvency II (which is distinct for regulatory reasons), these are generally the most detailed and most computationally intensive functions. Finally, only the very smallest firms use the same models for all functions. Note that throughout this question, Solvency II responses have been deleted to protect the confidentiality of survey participants.

The following table depicts the respondents based on their quantitative classification from earlier in the survey:

Function	Percent of Yes Respondents	Percent of "Quantitative" Respondents	Percent of "Non-Quantitative" Respondents
We use same models for all functions.	13.6%	0.0%	27.3%
Asset adequacy analysis/cash flow testing/reserve adequacy	86.4%	90.9%	81.8%
Product development and pricing	81.8%	90.9%	72.7%
Financial forecasting	81.8%	100.0%	63.6%
Determination of capital adequacy	81.8%	90.9%	72.7%
Asset-liability management (ALM)	77.3%	90.9%	63.6%
Economic capital	68.2%	100.0%	36.4%
NAIC C-1 RBC	63.6%	72.7%	54.6%
Valuation	54.6%	54.6%	54.6%
Embedded values	50.0%	54.6%	45.5%
M&A/actuarial appraisals	36.4%	36.4%	36.4%
Value at risk (VaR)	31.8%	54.6%	9.1%
Credit-adjusted value at risk (credit VaR)	31.8%	54.6%	9.1%
Risk-adjusted return on capital (RAROC)	27.3%	27.3%	27.3%

Firms with more quantitative credit modeling approaches are at least as likely to utilize credit analysis in each and every function. Once again, the largest gaps appear to be for financial forecasting, VaR, credit VaR, economic capital, and ALM. These functions require more computing resources, more robust risk management applications, and often require Monte Carlo simulation. With this in mind, it is not surprising that we see larger firms and firms with more quantitative models as more likely to apply credit models to these functions.

Function	Historical	Factor-Based Models	Actuarial Models	Credit Migration Models	Reduced Form Models	Structural Models	Proprietary or Internally Developed	Other
We use same models for all functions.	66.7%	33.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Product development and pricing	44.4%	50.0%	0.0%	5.6%	0.0%	0.0%	0.0%	0.0%
Valuation	25.0%	58.3%	8.3%	8.3%	0.0%	0.0%	0.0%	0.0%
Asset adequacy analysis/cash flow testing/reserve adequacy	36.8%	52.6%	5.3%	5.3%	0.0%	0.0%	0.0%	0.0%
M&A/actuarial appraisals	50.0%	37.5%	0.0%	12.5%	0.0%	0.0%	0.0%	0.0%
Financial forecasting	38.9%	33.3%	5.6%	16.7%	0.0%	5.6%	0.0%	0.0%
Determination of capital adequacy	33.3%	33.3%	11.1%	11.1%	0.0%	5.6%	0.0%	5.6%
NAIC C-1 RBC	42.9%	50.0%	7.1%	0.0%	0.0%	0.0%	0.0%	0.0%
Economic capital	13.3%	6.7%	20.0%	20.0%	6.7%	26.7%	0.0%	6.7%
Risk-adjusted return on capital (RAROC)	50.0%	0.0%	33.3%	0.0%	16.7%	0.0%	0.0%	0.0%
Embedded values	36.4%	27.3%	27.3%	9.1%	0.0%	0.0%	0.0%	0.0%
Value at risk (VaR)	0.0%	14.3%	28.6%	28.6%	0.0%	14.3%	0.0%	0.0%
Credit-adjusted value at risk (credit VaR)	0.0%	0.0%	14.3%	28.6%	14.3%	28.6%	14.3%	0.0%
Asset-liability management (ALM)	29.4%	47.1%	11.8%	5.9%	0.0%	0.0%	5.9%	0.0%

The table above depicts the percentage of respondents that use the indicated modeling methodology for each function. Note that the percentiles are based on the total number of respondents that perform the indicated function. In general, most firms conduct historical or factor-based analysis for all functions, while the more quantitative approaches (credit migration, reduced form, and structural models) appear in computation or simulation-heavy contexts, such as VaR, credit VaR, RAROC, and economic capital. In fact, only 20 percent of the firms conducting economic capital analysis and only 14 percent of firms conducting VaR analysis use historical or factor-based methods.

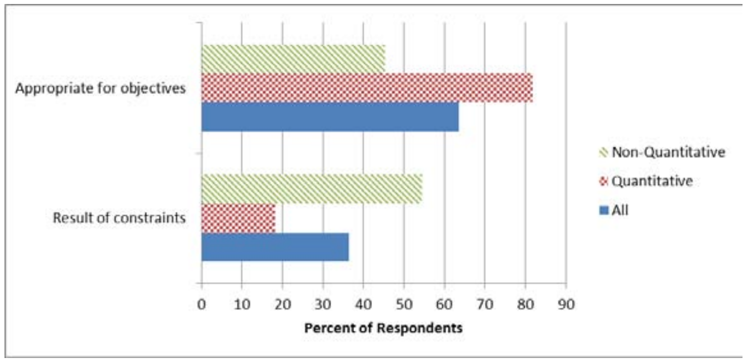
The following table details the size of the firms performing various functions with and without multiperiod models. Note that the respondent rates in the second column reflect the percentage of respondents who perform the function *and* also use multiperiod models.

Asset size is measured in millions of USD.

Function	Percent of Respondents that Perform Indicated Function that Also Use Multiperiod Models	Mean Size with Multiperiod Models	Mean Size without Multiperiod Models
We use same models for all functions.	50.0%	795	2,093
Economic capital	64.3%	75,149	54,563
Embedded values	63.6%	55,246	76,139
Asset adequacy analysis/cash flow testing/reserve adequacy	61.1%	60,935	51,431
Asset-liability management (ALM)	58.8%	73,735	40,341
M&A/actuarial appraisals	57.1%	29,052	73,508
Credit-adjusted value at risk (credit VaR)	57.1%	65,026	151,618
Financial forecasting	56.3%	69,517	51,929
Determination of capital adequacy	55.6%	53,962	60,652
Product development and pricing	50.0%	69,473	50,488
Valuation	50.0%	43,110	47,270
Risk-adjusted return on capital (RAROC)	50.0%	37,434	63,937
Value at risk (VaR)	50.0%	44,706	111,134
NAIC C-1 RBC	30.8%	25,975	71,547

Multiperiod model usage seems to be more mixed, with larger firms more likely to conduct multiperiod analysis for product development, asset adequacy, forecasting, economic capital, and ALM, and smaller firms more likely for M&A, C-1 RBC, RAROC, embedded values, VaR, and credit VaR (the asset size spread for the last two being particularly large). However, given the generally multiperiod nature of pricing, asset adequacy analysis, financial forecasting and ALM, it is surprising that so many firms do not use multiperiod credit models. This could mean that an unchanging credit model (static credit loss) is used for all periods in these multiperiod exercises.

Q27: In your opinion, are different modeling approaches to credit losses appropriate for different objectives/functions, or is use of different approaches largely a result of time, data or institutional constraints?



Most firms indicated that different modeling approaches are appropriate for different objectives or types of analysis. The response rate did not vary dramatically by an organization's size (output omitted), though the quantitative nature of a firm's credit models appeared to have a non-trivial effect on the firm responses. Amongst non-quantitative firms, the responses were almost evenly split between whether or not different approaches were appropriate, or were the result of constraints of one form or another, while quantitative firms quite strongly believed that different modeling approaches were appropriate and the result of specific intent within the organization.

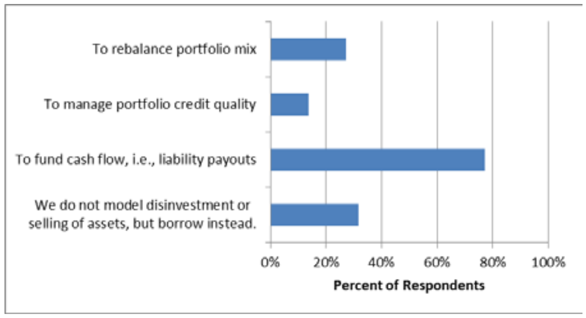
Other Aspects of Credit Models

Q28: Does the company's credit risk modeling methodology vary by asset class? Please complete the following table.

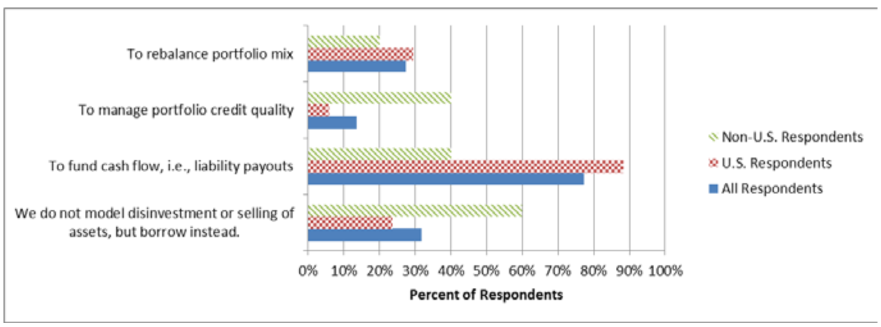
Asset Class	None—Defaults Not Material	Historical Credit Assessment	Factor-Based Approach	Actuarial Credit Models	Credit Migration Model	Reduced Form Models	Structural Model	Proprietary Internal Models	Other Models (Non-Internal)
We use same models for all asset classes.	0.0%	30.8%	23.1%	7.7%	0.0%	0.0%	7.7%	0.0%	0.0%
U.S. Treasuries	71.4%	0.0%	14.3%	0.0%	0.0%	14.3%	0.0%	0.0%	0.0%
Sovereigns other than U.S. Treasuries	28.6%	0.0%	14.3%	0.0%	28.6%	14.3%	0.0%	0.0%	0.0%
Agency structured securities (MBS)	42.9%	14.3%	28.6%	0.0%	14.3%	0.0%	0.0%	0.0%	0.0%
Private label structured securities—MBS	0.0%	28.6%	14.3%	0.0%	14.3%	0.0%	14.3%	0.0%	28.6%
Private label structured securities—ABS	0.0%	28.6%	14.3%	0.0%	14.3%	0.0%	14.3%	0.0%	28.6%
Private label structured securities—CMBS	0.0%	28.6%	14.3%	0.0%	14.3%	0.0%	14.3%	0.0%	28.6%
Direct or whole residential mortgages	60.0%	0.0%	20.0%	0.0%	20.0%	0.0%	0.0%	0.0%	0.0%
Direct or whole commercial mortgages	0.0%	25.0%	25.0%	0.0%	0.0%	12.5%	25.0%	0.0%	0.0%
Direct or whole agricultural mortgages	80.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Other public bonds	0.0%	0.0%	25.0%	0.0%	25.0%	12.5%	25.0%	0.0%	12.5%
Other private bonds	0.0%	0.0%	25.0%	0.0%	25.0%	12.5%	25.0%	0.0%	12.5%
Other	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%

Following on Q27 regarding the appropriateness of different modeling techniques, Q28 characterizes those techniques across asset classes. We see that credit is a material concern for most forms across every asset class, with the notable exceptions of U.S. Treasuries and possibly agency structured securities and whole residential mortgages (somewhat surprisingly). Beyond those products, respondents seem roughly evenly split across approaches. We often see the same proportion of firms engaging in factor-based models as credit migration, reduced form and structural models, though historical credit assessment seems to be a more common response for most asset classes.

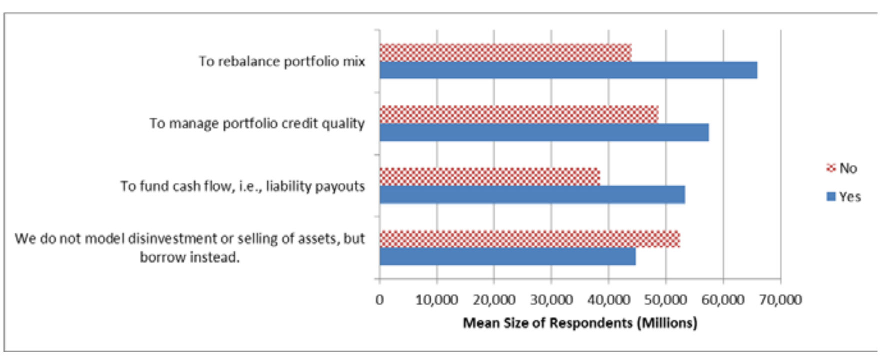
Q29: Under what conditions does the company model disinvestment or selling of assets?



Unlike many other questions in the survey, response rates to this question did not seem to vary by the firm's use of quantitative or non-quantitative models. However, there do appear to be some differences between U.S. and non-U.S. firms:



U.S. firms seem more likely to model disinvestment in any manner, and typically use disinvestment to fund liability payments. In contrast, non-U.S. firms appear more likely to rebalance the portfolio to address dynamic credit concerns. We can also see that firm size plays an important role, with larger firms more likely to model disinvestment in any manner:



Q30: What assumptions are used to model disinvestment or selling of assets?

Disinvestment Assumptions	Percent of Respondents
Fixed income investments are sold assuming changes to the underlying Treasury curve.	72.7%
Fixed income investments are sold assuming credit spreads have changed.	31.8%
Equities are sold at valuation date market value plus assumed deterministic growth rate.	22.7%
Equities are sold at valuation date market value plus assumed stochastic growth rate.	22.7%
Derivatives are sold assuming potentially changing swap spreads to Treasuries.	18.2%
Derivatives are sold assuming constant swap spread to Treasuries.	13.6%
Equities are sold at valuation date market value.	9.1%
Fixed income investments are sold assuming credit rating can change through the use of transition matrices.	9.1%
Assets are sold at book value.	4.6%

Most firms model fixed income disinvestment by allowing at least the underlying risk-free rate to change and assuming a fixed credit spread to determine "market value." However, over 40 percent of respondents report allowing spreads to change either deterministically or through ratings transition matrices. For equities, firms appear much more likely to embed a growth rate in their calculations, either fixed or stochastic, than to assume they are disposed of at current market values.

Disinvestment Assumptions	Percent of Respondents	Percent of “Quantitative” Respondents	Percent of “Non-Quantitative” Respondents
Fixed income investments are sold assuming changes to the underlying Treasury curve.	72.7%	63.6%	81.8%
Fixed income investments are sold assuming credit spreads have changed.	31.8%	27.3%	36.4%
Equities are sold at valuation date market value plus assumed deterministic growth rate.	22.7%	18.2%	27.3%
Equities are sold at valuation date market value plus assumed stochastic growth rate.	22.7%	18.2%	27.3%
Derivatives are sold assuming potentially changing swap spreads to Treasuries.	18.2%	27.3%	9.1%
Derivatives are sold assuming constant swap spread to Treasuries.	13.6%	18.2%	9.1%
Equities are sold at valuation date market value.	9.1%	9.1%	9.1%
Fixed income investments are sold assuming credit rating can change through the use of transition matrices.	9.1%	18.2%	0.0%
Assets are sold at book value.	4.6%	0.0%	9.1%

Quantitative firms seem more likely to utilize transition matrices to model spread evolution, and are more likely to model derivative disinvestment; but, somewhat interestingly, are less likely to model disinvestment in almost every other category than non-quantitative firms.

Q31: What types of sensitivity testing are performed for credit risk?

Asset size is measured in millions of USD.

Sensitivity Tests	Percent of Respondents	Mean Size of Yes Respondents	Mean Size of No Respondents
Increasing default rates for all asset classes	77.3%	53,161	39,049
Increasing credit spreads	45.5%	61,850	40,039
Within the projection, temporarily increasing the default rates	36.4%	66,735	40,364
Decreasing recovery rates	31.8%	92,455	30,119
Increasing credit migration to lower quality	27.3%	102,281	30,331
Increasing default rates for some asset classes	22.7%	60,441	46,869
Macroeconomic factor sensitivity testing	22.7%	93,801	37,057

Once again, we see that larger firms are more likely to conduct any given sensitivity test, particularly recovery rate, migration rate, and macroeconomic factor tests. We see similar highlights when we look at firms based on their modeling approaches:

Sensitivity Tests	Percent of Respondents	Percent of "Quantitative" Respondents	Percent of "Non-Quantitative" Respondents
Increasing default rates for all asset classes	77.3%	81.8%	72.7%
Increasing credit spreads	45.5%	45.5%	45.5%
Within the projection, temporarily increasing the default rates	36.4%	36.4%	36.4%
Decreasing recovery rates	31.8%	54.6%	9.1%
Increasing credit migration to lower quality	27.3%	54.6%	0.0%
Increasing default rates for some asset classes	22.7%	36.4%	9.1%
Macroeconomic factor sensitivity testing	22.7%	36.4%	9.1%

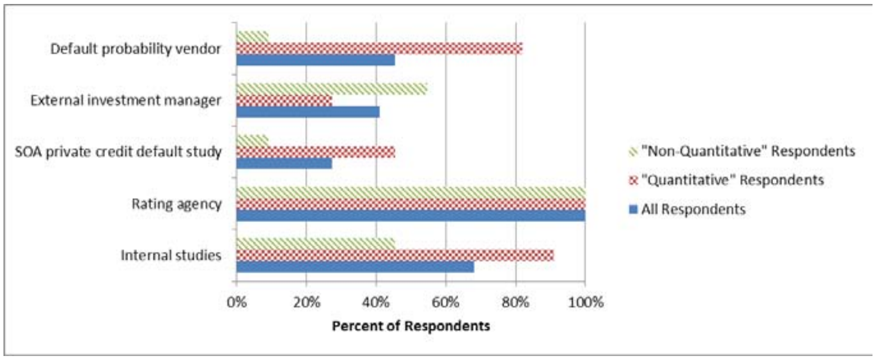
Quantitative firms are more likely to conduct each and every sensitivity test, particularly recovery rates, credit migration rates and macroeconomic factor testing, than non-quantitative firms.

Sensitivity Tests	Percent of Respondents	Percent of U.S. Respondents	Percent of Non-U.S. Respondents
Increasing default rates for all asset classes	77.2%	70.6%	100.0%
Increasing credit spreads	45.5%	35.3%	80.0%
Within the projection, temporarily increasing the default rates	36.4%	35.3%	40.0%
Decreasing recovery rates	31.8%	29.4%	40.0%
Increasing credit migration to lower quality	27.3%	17.6%	60.0%
Increasing default rates for some asset classes	22.7%	11.8%	60.0%
Macroeconomic factor sensitivity testing	22.7%	29.4%	0.0%

We see a similar pattern by provenance as well. While the sample size for European and Canadian firms is smaller than for the quantitative/non-quantitative distinction in the previous table, we see that non-U.S. firms are more likely to engage in every kind of sensitivity testing, save for macroeconomic factor-based tests, where no non-U.S. respondents reported engaging in this activity.

Assumptions/Factors/Variables

Q32: Which of the following are sources of data used for any type of credit risk modeling at the company?



Source	Percent of Respondents	Size of Yes Respondents	Size of No Respondents
Internal studies	68.2%	63,770	20,346
Rating agency	100.0%	49,954	N/A
SOA private credit default study	27.3%	75,131	40,512
External investment manager	40.9%	56,902	45,143
Default probability vendor	45.5%	83,152	22,288

Larger firms more likely to use all sources: this suggests that larger firms have a more diverse pool of information to draw upon than smaller firms. Moreover, this seems to be related to the quantitative nature of the model approach as we have seen throughout this survey. Firms with more quantitative models are much more likely to have internal or private studies, as well as purchase credit inputs from a third-party vendor.

Q33: For your purposes, what do you believe are the strengths and weaknesses of the commonly used sources of historical default data used to develop assumptions and calibrate parameters?

Respondents here agreed that agency ratings were very useful in the corporate space, as they are readily available, generally accepted and widely recognized within that asset class. However, most survey respondents stated that the lack of transparency, questionable usefulness of historical data, erratic performance and limited coverage outside of the corporate space were large drawbacks to Nationally Recognized Statistical Rating Organization (NRSRO) ratings in the credit space.

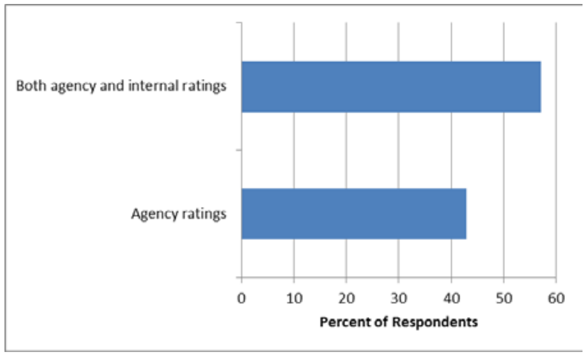
Finally, respondents specifically highlighted the low statistical performance of agency ratings when assessing default risk (particularly in the non-corporate context), as well as their inability to accommodate macroeconomic factor-based stress testing.

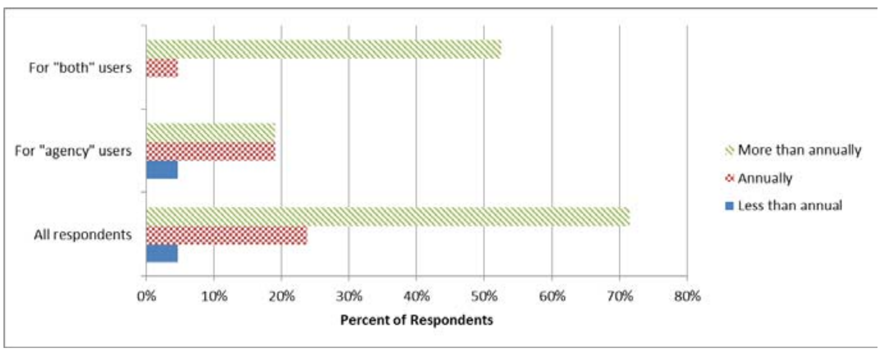
Q34: Do macroeconomic variables, such as unemployment, interest rates or interest rate volatilities, influence credit risk losses in the company's models?

Macroeconomic Variables	Percent of Respondents	Percent of "Quantitative" Respondents	Percent of "Non-Quantitative" Respondents
Treasury interest rates	45.5%	54.5%	36.4%
Risky interest rates (e.g., BAA Spreads, yield on 30-Yr fixed mortgages, etc.)	45.5%	54.5%	36.4%
Macroeconomic variables are not used in the company's loss models.	36.4%	36.4%	36.4%
Equity/equity index prices	36.4%	54.6%	18.2%
Interest rate volatility	27.3%	18.2%	36.4%
Equity/equity index volatilities	27.3%	27.3%	27.3%
Unemployment rates	22.7%	27.3%	18.2%
Real or nominal gross domestic product	22.7%	36.4%	9.1%
Inflation rates	18.2%	9.1%	27.3%
Residential real estate prices	18.2%	27.3%	9.1%
Commercial real estate prices	18.2%	36.4%	0.0%
Interbank interest rates	9.1%	18.2%	0.0%
Foreign exchange	9.1%	18.2%	0.0%
Consumer confidence indices	9.1%	18.2%	0.0%
Commodity prices	0.0%	0.0%	0.0%

Quantitative firms seem more likely to incorporate almost every macroeconomic factor listed in this survey, with the largest differences seen in equity and real estate prices. The only exceptions to this pattern are inflation rates and interest rate volatilities.

Q35: To the extent that the company's modeling uses credit ratings, whose credit ratings do you use—an agency rating, an internal rating, or both?
Q36: How often are these ratings updated?





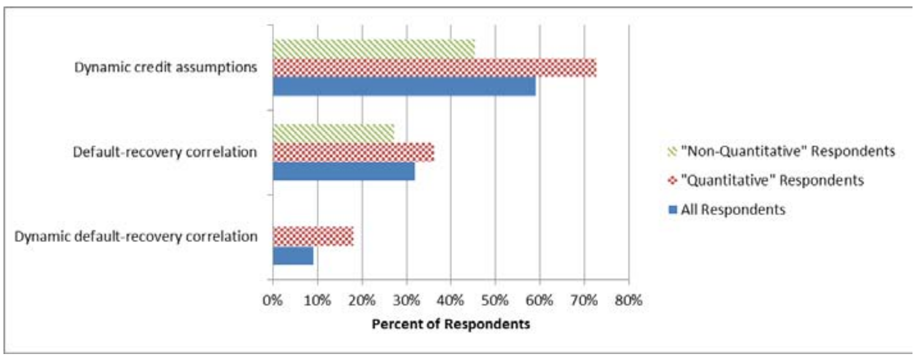
The movement to internal ratings in addition to NRSRO assessments comes alongside a movement to more frequent ratings updates. This may be causal: the desire for more up-to-date information in credit quality may lead organizations to develop and implement their own internal credit assessments updated at the frequency of their choosing.

Q37: What types of provisions for adverse deviation are used in the company's credit loss assumptions?

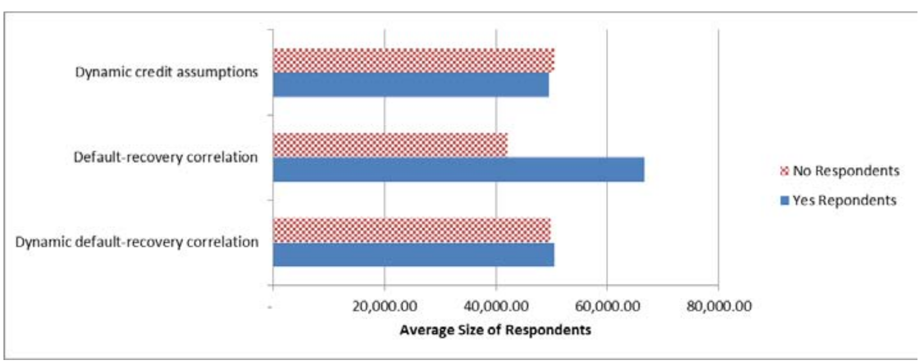
Note that this question only had 21 respondents:

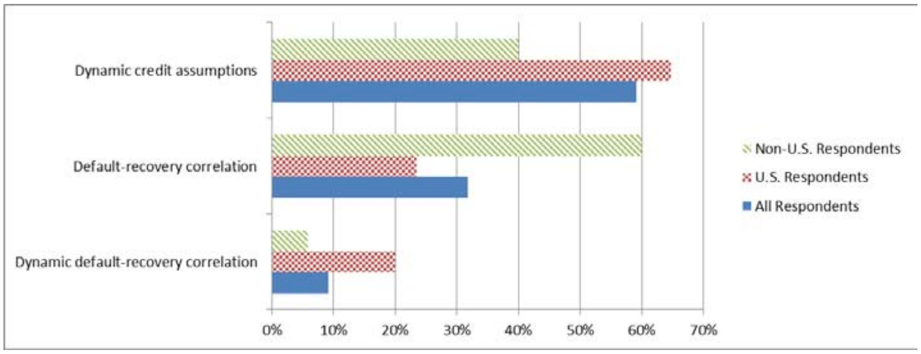
A surprisingly high percentage of respondents report no provision for adverse deviation. A full one-third of organizations do not generate these calculations whatsoever, equal to the number who use the percentage of expected loss and any other method. While there do not appear to be any patterns based on the quantitative nature of the respondent's credit models, all of the respondents with no provision for adverse deviation calculations are from the United States.

Q38: In multiperiod models, do credit assumptions vary (either explicitly or endogenously) throughout the credit cycle, or is a single fixed rate or average rate used over the full credit cycle?
Q39: Do any of the credit modeling assumptions used at the company utilize correlation either explicitly or endogenously between default and recovery rates?
Q40: If not, why not?
Q41: Is the default-recovery correlation allowed to vary over time or across scenarios?



Quantitative firms are more likely to have dynamic credit assumptions, include default and recovery correlation, and have that correlation vary over time. In fact, no non-quantitative firms perform analysis with dynamic default recovery correlation. Unlike other measures of model or application complexity included in this survey, these effects are not readily visible when we cut based on firm size or provenance:

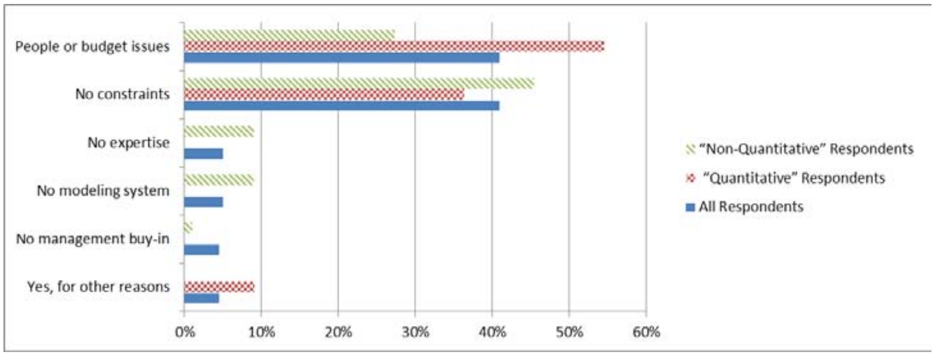




Dynamic credit assumptions
Default-recovery correlation
Dynamic default-recovery correlation
0%
10%
20%
30%
40%
50%
60%
70%
Non-U.S. Respondents
U.S. Respondents
All Respondents

Future Modeling

Q42: Is your current modeling constrained in any way?



Most firms report either no constraints in their current modeling approach, or people or budget issues. Within these two responses, non-quantitative firms are more likely to report that they face no constraints, and quantitative firms are more likely to cite people and budget issues. Of the five non-quantitative firms (45 percent) that responded "no constraints," four of the five responded in Q44 that they have no future planned improvements in their credit risk modeling either. These authors find it surprising that non-quantitative methods appear to be deemed sufficient by these companies, especially given what has happened in the economy over the last five to 10 years. Very few respondents cite managerial, expertise, or modeling system concerns, though this is somewhat difficult to reconcile with the anticipated challenges discussed in Q46.

Q43: In a few sentences, how would you summarize "best practice" in credit risk modeling?

The general characterization of "best practice" seemed to have several common elements:

- Multiple credit models that include a wide range of risk drivers—idiosyncratic, market and macroeconomic—and have the capability to examine the sensitivity of each on the cash flow and credit risk of each security and the portfolio.
- Models that can reflect a range of correlations assumptions between key risk drivers, e.g., asset or default correlation, probability of default, loss given default, and correlations.
- Models that have the ability to examine risks under multiple time horizons, including multistep horizons, and at a variety of confidence intervals. Expected loss and unexpected loss are produced. Tail-risk methodologies in addition to standard credit VaR approaches are necessary.
- Stochastic models with the ability to produce full loss distributions and perform stress tests.
- Model in an integrated asset/liability framework providing cash flow and market value over a multiperiod horizon with probability of default, loss given default, transitions, and credit spreads varying by time period.
- Key assumptions and the models themselves are understood by modelers and management and actionable information is provided.

"Best practice" modeling also includes recognition of specific economic conditions and macroeconomic variables, measurement at the security level, stochastic loss distributions separated by probability of default and loss given default, correlations amongst securities, and credit migration. One company reminds us that transparency, documentation and auditability are critical. Finally, five companies provided no response.

While the comments were similar, "quantitative" firms seemed to have more specific or more detailed descriptions of "best practice" modeling than "non-quantitative" firms. Quantitative firms were more likely to respond as well: out of the five firms that did not offer a response, only one of them was from a firm with more quantitative credit modeling techniques.

Complete Responses:

<u>Non-Quantitative Firms:</u>

— No response (4)

— Dynamic, scenario-based frequency and severity of credit losses reflecting the specific economic conditions at each time period within each scenario. This would require the ability to calibrate a probability distribution of default for each security held within various economic scenario states, a distribution of severity given default, and ideally correlations between securities within the portfolio.

— Best practices—that is, the level of sophistication—fit the circumstances of the organization and the needs of the function. Actuarial valuation and product management may reasonably be less sophisticated as these typically seek to make adequate provision for losses over a long term. Portfolio management and ERM (especially capital management) might require greater sophistication.

- Best practice is any approach that reasonably measures credit risk impact in your business. Product lines that are significantly exposed to credit losses should employ models that include such events, whereas simple approaches might be perfectly adequate for other lines.

- Credit modeling should include consideration of probability of default and recovery rates, and should include stochastic modeling and deterministic stress testing with correlations to credit spreads and other macroeconomic variables.

- Best practice would involve modeling the actual assets using a stochastic process, including economic scenarios, using appropriate assumptions and models.

- Transparent methodology and detailed documentation. Strong control and auditing. Reflect the change in economic conditions under different stochastic scenario paths. Tie to other macroeconomic variables. Calibrate to actual experience.

- Credit risk modeling has to encompass credit migration. The biggest risk we saw during the financial crisis was contagion. Bonds that in normal times were rated investment grade were downgraded rapidly to junk. In a fully integrated credit risk model, that would be captured via credit rating migration and probability of incidence. Modeling constraints and expertise tend to be obstacles for many companies, and often averages are used that can mask results.

<u>Quantitative Firms:</u>

- No response (1)

- While there is no single "best practice" for credit risk modeling, leading practices would include having the following capabilities:

    - Models that include a wide range of risk drivers—idiosyncratic, market and macroeconomic—and have the capability to examine the sensitivity of each on the credit risk of the portfolio.
    - Models that can reflect the range of correlations assumptions between key risk drivers, e.g., asset or default correlation, PD (probability of default) and LGD (loss given default) correlations.
    - Models that have the ability to examine risks under multiple time horizons, including multistep horizons, and at a variety of confidence intervals. Tail-risk methodologies in addition to standard VaR approaches are necessary.
    - Leading firms reduce model risk and strengthen analysis by employing multiple models that might be quite different in construction—e.g., reduced form + Merton + CDS/EDFs (credit default swaps/estimated default frequencies)—and examining similarities and differences between them.

- A robust credit risk process requires a broad assessment of the portfolio encompassing diversification at the asset class, country, sector and issuer level. Expected PDs and LGDs, in both base case and stressed scenarios, must be examined, utilizing a framework that takes correlation into consideration.

- I believe best practices are to have modeling to capture the diversification, correlation and leverage benefits within the portfolio. Need to have robust internal rating system, credible experience data, and the right people and tools to communicate the total credit risk being taken and the impacts to credit risk of different hedging and/or investment decisions.

- Not sure.

- Credit risk modeling should cover normal and stressed conditions at transaction and portfolio level. Transaction level factors should include exposure, probability of default, loss given default and asset cash flow. Portfolio level factors should include unexpected loss and correlation. Model measures should include expected loss, unexpected loss and credit VaR.

- To model credit risk in an integrated asset-liability framework.

- Start with the basic inputs, default probabilities and recovery. This sets the expected loss needed for planning. Look at different correlation structures to create a loss distribution. Look at the output distribution to see reasonableness as measured against historical as best judged. Correlate results to economic scenarios of equity and interest rate moves. Stress tests to see which assets are most sensitive. Do fundamental look to try to anticipate problem areas which don't show up in the historical numbers. Also, separate default estimates from market value movements.

- Credit risk should be modeled using asset-specific information such as current rating, seniority, and remaining pattern of cash flows. Stress testing should consider macroeconomic stress and contagion rather than independence of defaults. Modelers should be able to explain key assumptions and modeling techniques to senior management.

- Best practice in credit risk modeling involves utilizing a sophisticated range of credit models that can be fully understood by the modelers and explained to stakeholders.

-
  1. It is forward-looking, reflecting the current market price of risk;
  2. It is dynamic and promotes collaborative efforts within the insurance product management/investment/risk management;
  3. It is granular and flexible, capable of identifying the hot spots; and
  4. Lastly, actionable.

Q44: Please list the company's planned improvements in credit risk modeling over the next two years.

We summarize common responses to Q44 below.

Again, we see differences in responses across firms based on their "quantitative" or "non-quantitative" credit modeling approaches. For non-quantitative companies, planned improvements include expanding stochastic modeling activities and allowing default rates to vary over time. However, most non-quantitative companies have no specific planned improvements or did not provide a response. With respect to quantitative companies, two are actively implementing credit-risk vendor packages, while one company is developing an in-house structural model. Other planned improvements include simulation of derivative counterparty risk, additional stress testing and scenario analysis, decomposition of credit spreads, updating of probability of default and loss given default as well as their correlation, and creation of loss distributions using economic scenarios. Two companies had no response to this question.

The disparate response between quantitative and non-quantitative companies highlights inertial concerns. The quantitative companies, despite their relatively more sophisticated approaches to credit, appear to have a stronger desire for credit modeling improvements and list more activity in this regard.

Complete Responses:

Non-Quantitative Firms:

- No response (4)
- No planned improvements.
- No specific planned improvements. However, we do seek continuous improvement in our processes, and this is a potential area of emphasis especially in light of internal focus on ERM. Improvement is likely to be initiated by investment department before it would migrate to actuarial processes.
- We will pay attention to our model system vendor's approach to credit risk modeling, but have no plans to change our modeling at this time.
- We plan to stochastically model our actual assets using a consistent set of economic scenarios.
- We have traditionally used historical default rates by rating class and held this constant throughout the projection (except for stress tests). There's a good case to be made that not all AAA bonds (for example) stay AAA throughout a 30-year projection, and so the default rate ought to increase with time.
- Expand stochastic modeling.
- No improvements specifically planned for credit risk modeling. However, there are broader discussions to improve asset modeling, and credit risk could become part of the project.

Quantitative Firms:

- No response (2)
- Enhancing contingent credit risk modeling framework to include full simulation of derivative counterparty risks, including netting and collateral and more formally including the analysis of credit risks under various time horizons (1-yr, 3-yr, 5-yr) consideration.
- Currently, we are in the process of implementing [a vendor package] for credit risk modeling and [a vendor package] for economic capital and integrated risk modeling. Using these tools, we will also enhance stress testing and scenario analysis.
- Plan to quantify credit risk under Basel approaches to be able to compare and contrast it with insurance regulatory approach as well as internal-based approaches. Plan to update our various studies for default assumptions, recovery assumptions and correlation assumptions. Hope to move to a system to model all asset classes at the same time and incorporate macroeconomic variables.
- Develop in-house structural credit model to model fixed income and equity assets.
- We are implementing [a vendor package] for all asset classes. The output distributions will be correlated with other activities in our economic capital and pricing frameworks.
- Decompose the credit spreads observed on the market into spread components which cover expected default losses, unexpected default losses and liquidity premiums.
- Reassess the probability of default inputs and LGD for certain asset classes. Look at PD-Recovery correlation.
- We plan to subscribe to a rating agency database on historical downgrades/defaults/recoveries that will allow us to develop assumptions that vary by sector on our bonds.
- Many functions in the [business unit] currently utilize simplistic, factor-based credit modeling. The economic capital unit (which exists at the corporate level, outside of the [business unit]) utilizes a much more sophisticated model with credit losses and distributions that vary by economic scenarios. The [business unit] has started making use of the more sophisticated models in some efforts and intends to do so more completely over the next two years.
- Implementing default/recovery correlation model, scenario analysis, risk aggregation with the other risks like equity and ALM.

Q45: What are the primary drivers of the company's planned improvements?
Q46: What challenges do you anticipate when implementing the model improvements listed above?

Source	Percent of Respondents
Desire to move to best practice	68.2%
Internal constituents	54.6%
Regulators	36.4%
Rating agencies	36.4%
Competitors in the industry	27.3%
External auditors	18.2%
Wall Street analysts	4.6%
Third-party consultants	0.0%

Potential Issues	Percent of Respondents
Modeling software does not exist and needs to be built	54.6%
Scarce actuarial resources	45.5%
Management buy-in	36.4%
No/insufficient budget dollars to accomplish improvement	31.8%
Scarce IT resources	31.8%
Other (please specify)	
Industry overreliance on C1RBC	4.6%
Data quality	4.6%

Most survey respondents report that they wish to improve their existing methods because of a desire to move to "best practice" calculations: that there are more reliable or more appropriate tools available. However, the most frequently cited impediment to this process is that modeling software does not exist. Surprisingly, this far exceeded the relative importance of managerial and budget concerns. However, elsewhere in the survey, several firms reported that they are moving to new third-party solutions to accommodate new methodologies, and very few firms indicated that they presently felt constrained by their modeling system. Given these facts, there may be a need to facilitate communication between organizations regarding their risk management tools and solutions.

Conclusion

This paper describes the evolution of credit research in both academic and life insurance industry journals and surveys life insurance companies in the United States, Canada, and U.S. subsidiaries of European insurers on their current practices involving credit risk analysis. We have detailed how the focus of the literature has evolved over time to gradually incorporate credit into more types of analysis and more securities, the relative merits of different approaches in different contexts, how credit is modeled by the industry, and several papers that flag concerns or issues with particular models, approaches, or common practices, though the main thrust of this work is to describe the current credit modeling techniques within the insurance industry.

From the responses to the survey, we see a variety of approaches to credit risk. Firms characterize credit risk through several different models and modeling approaches, including factor-based models, historical credit assessments, credit migration models, structural or reduced form models, or other or proprietary solutions. Factor-based models tend to be relatively easy to implement, with readily available adjustment factors, though these models do not easily permit accurate analysis or the potential distribution of credit losses, which include capital and VaR-style analytics. Firms engaging in factor- based models were smaller, with less complex portfolios; these traits are broadly consistent with the advantages and disadvantages of factor-based approaches. The analysis that survey respondents performed most often was historical credit assessment based on internal or NRSRO rating data. Of course, these ratings were almost always only available for a strict subset of their portfolio, and almost all survey respondents expressed some concern about their future reliability in part because of the performance of ratings during the 2007–2009 period. That said, these indicators remain an industry standard, though most firms engage in some validation or cross-checking exercise. Based on the available information regarding the regulatory environment, we expect this trend to accelerate in the coming months and years.

The various approaches to credit risk in this survey have their own strengths, as well as their own limitations. Both factor-based and historical methods are based on static credit analytics: without substantial additional structure, they are not amenable to changing credit conditions over a period of time. Instead, to model changing credit conditions, firms must incorporate some form of a dynamic model, such as credit migration, structural or reduced form models. Credit migration models are fairly straightforward extensions to ratings or scoring frameworks, though the firm would have to parameterize some form of transition matrix. Structural models of credit behavior often have some intuitive appeal based on the structural framework, but are generally difficult to parameterize as the model drivers are not always observable (such as the value and volatility of assets in Merton (1974)), and the empirical performance is often lacking. Reduced form models can flexibly employ a wide variety of explanatory variables, including macroeconomic data, to characterize credit behavior at any point in time, but require a substantial amount of representative and reliable historical data to be useful. More recent work illustrates that reduced form models have higher performance than other types when data is available. Due to the complexity of these models and the need for testing and possibly parameterization, they are used only by the largest firms with the most complex portfolios.

Deterministic methods do not appear adequate for all credit risk modeling purposes. Both the literature search and the company survey indicate that stochastic models are important tools for functions where understanding the distribution of credit losses is important, for example credit VaR. Modern credit technology, the structural models and reduced form models that are being implemented by some companies are not deterministic. However, both the researchers and several survey respondents believe that different approaches to credit loss modeling are appropriate for different modeling objectives. The credit model that should be used depends on the nature of the question being asked. For example, while they may not represent the most modern of risk technologies, deterministic models should continue to have a role in a company's credit risk modeling. It depends on the nature of the function being performed and the relative accuracy desired. Stochastic models would be excessive if the function modeled was simply looking for an expected value on a short-term product that included little asset risk.

The survey also inquired about how respondents modeled disinvestment or selling of assets to get at the issue of spread changes. While 32 percent of respondents model credit spread changes in disinvestment of assets, only 9 percent model credit spread changing through rating transition. Selling troubled assets at losses before the actual default events would imply that there has been some type of rating transition. Very few companies appear to be modeling and monitoring this type of credit loss and, as a result, could be missing a significant source of potential losses. Respondents were asked how they incorporate macroeconomic variables into their credit analytics. There is substantial regulatory interest in this area, and most organizations are particularly interested in models with macroeconomic sensitivity after the 2008 recession and slow recovery. Still, 36 percent of survey respondents said that macroeconomic variables, such as interest rates, do not affect their credit risk modeling in any way. We strongly believe that capital loss assumptions should vary by scenario based on their portfolio's credit loss sensitivity to the macroeconomic variables that drive and define the scenario.

The particular modeling approach selected by a firm is correlated with many observable characteristics and economic behaviors. Firms with more quantitative, dynamic approaches seem to be larger, to hold different portfolios, engage in different analytics, incorporate more transaction information, and run more types of analyses and more stress tests with more macroeconomic information. Firms with more quantitative approaches to credit hold more structured products, more commercial mortgages, more private firm loans, and less public debt. However, any causal argument here could plausibly go in either direction: the more intricate credit analytics were implemented because of a desire to invest in different securities, or that heterogeneous endowments of particular holdings incite a desire for more appropriate modeling techniques, though by construction, we would highlight that increased access to these markets would increase the size of an organization’s investment opportunity set, which would potentially permit either higher returns, less risk, or both. Quantitative firms are much more likely to perform all types of credit inquiry, including deterministic analysis, stress testing and stochastic analysis. They are more likely to incorporate credit into spread simulation, examine concentration and settlement risks, as well as sovereign risk. Firms with migration, structural or reduced form models are more likely to calculate or simulate a full distribution of losses, which affords them the opportunity to generate more types of analyses, including detailed forecasting, economic capital, ALM, as well as VaR and credit VaR. They also include stress tests of more credit components, such as recovery rates, migration speeds, and macroeconomic variables, and are more likely to include almost every common macroeconomic variable in their credit analysis, which is particularly important given the trajectory of the regulatory requirements. They also report fewer constraints governing their chosen approach, which suggests that firms without these approaches realize that the credit analysis is meaningfully restricted from what would be "best practice."

Of course, the accuracy and reliability of the data used to develop assumptions is critical for all actuarial functions. Within the survey, respondents were specifically asked about the strengths and weaknesses of commonly used sources of historical default data. Respondents here agreed that agency ratings were very useful in the corporate space, as they are readily available, generally accepted, and widely recognized within that asset class. However, most survey respondents stated that the lack of transparency, questionable usefulness of historical data, erratic performance and limited coverage outside of the corporate space were large drawbacks to Nationally Recognized Statistical Rating Organization (NRSRO) ratings in the credit space. Finally, respondents specifically highlighted the low statistical performance of agency ratings when assessing default risk (particularly in the non-corporate context), as well as their inability to accommodate macroeconomic factor-based stress testing. In addition, 68 percent of respondents said that they used internal studies. These companies appear not to be relying totally on internal studies, as 100 percent of the respondents stated that they also use rating agency studies. As with any assumptions or parameterizations that rely on company-specific experience, the firm must decide if the company's historical experience is credible and relevant in the future, or in specific stress scenarios. This is especially important as there are comparatively few investment grade defaults in the industry.

Finally, the survey respondents, and the authors of this study, characterize "best practice" credit approaches with several common features. The sophistication of modeling depends on function or purpose and the nature and magnitude of credit risk in the portfolio.

- The institution should consult multiple credit models that include a range of risk drivers: idiosyncratic, market, and macroeconomic, and assess the resulting cash flows for each security through maturity and for the entire portfolio.
- The models should be transparent to facilitate understanding by modelers and management and encourage critical analysis regarding any and all model outputs.
- Models should be able to incorporate a range of correlation assumptions between any and all credit parameters, such as asset values, risk factors, default probability and recovery, etc.
- Models should be able to assess credit in a dynamic way over multiple time horizons at a variety of confidence intervals. This will help the institution characterize the potential timing and dispersion of cash flows.
- Particular attention should be paid to the sensitivity of tail estimates, such as credit VaR and economic capital, assumptions and initial conditions.
- Models should be able to incorporate stochastic simulations and stress tests with respect to variables and parameters of interest to management, to the board, and to regulatory agencies.

- The credit modeling framework should integrate the evaluation of assets and liabilities, projected cash flows, book values and market values to permit institution-wide analysis of the portfolio, the operations and any common sensitivities.

While it does not appear that any insurance company, or any financial firm, can reasonably claim to satisfy all of the elements of “best practice” above, some insurers are reasonably close to this standard. However, many—if not most—are not. Often, firms report that people or budget issues prohibit analysis that may be more intricate. Somewhat surprisingly, the most common response in this regard is that modeling software does not exist. Some companies may be unaware that the software does exist. A likely interpretation is that the models are not available within the company. Other interpretations of this response are that credit risk has not been a high priority or that the company considers a factor-based approach sufficient, and therefore not invested the resources on building/acquiring credit modeling software. Still, we see firms that are migrating to new software products and risk analysis firms over the next two years to accomplish these goals. The industry could benefit from increased communication amongst participants with respect to their preferred credit analysis software or consultants.

This survey illuminated industry behavior with respect to several dimensions of credit risk analysis. That said, many topics were deliberately out of scope. Two such areas are counterparty credit concerns and derivative securities, such as credit default swaps. There are many open questions in this space, such as: How are institutions monitoring and managing counterparty risk? How are any limits set, reviewed and adjusted? How are these products priced and modeled? How are counterparties selected for individual transactions? How does the institution integrate margin requirements in this domain with the other forms of risk analysis? Future research on industry credit risk practices may also want to focus on why certain organizations have different credit risk modeling approaches. From this survey, we know that more quantitative firms are larger; invest in more varied, and modeling-intensive, securities; and apply credit risk more broadly across the institution, but have left open the question of what leads firms to a develop and apply a more quantitative approach in the first place. Also of interest is how institutions have been able to navigate changes and additions to their modeling approach: we see that many firms plan on modifying and upgrading their approach to credit, though most are constrained by a variety of internal and external forces. The potential gains to individual firms, and to the industry as a whole, from relaxing these constraints may be quite large.

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